

On Mitigation of Ranging Errors for Through-the-Body NLOS Conditions using Convolutional Neural Networks

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Abstract— A UWB-based indoor localization is highly useful in various location-aware applications due to its high-precision and robustness in obstacles. However, it is still a challenging issue to mitigate ranging errors caused by non-line-of-sight(NLOS) conditions. In recent years, various approaches have been attempted using deep learning, but this is mostly the study of NLOS conditions by indoor obstacles. In this paper, we proposed a solution of ranging error mitigation for through-the-human body NLOS conditions using Convolutional Neural Networks.

Keywords— Ultrawideband (UWB), Ranging Error, Convolutional Neural Networks, NLOS Mitigation, Human Body NLOS.

I. INTRODUCTION

Various technologies such as Wi-Fi, Bluetooth, sound, infrared, and UWB have been used for indoor localization [1]. In particular, Impulse-radio ultra-wideband (IR-UWB) is a promising technology for high-precision indoor localization technology due to its various advantages such as low energy consumption, centimeter level precision, and robustness against to NLOS(Non-Line of Sight) due to characteristic of pulse signal and its wide bandwidth. Since this strength, UWB based localization system has been applied to various field such as indoor navigation system [2], Facility maintenance [3] and automobile to figure out car key's location [4]. In addition, UWB localization technology has begun to appear on latest mobile device such as Apple iPhone 11 Pro and Samsung Galaxy Note 20 Ultra, promising novel location-based services such as 'Find My' service.

In this context, most of the devices for the UWB based services are inevitably human carrying. When user hold device or in the user's pocket, some angles between UWB devices in all directions will always be obscured by human body such as wrists, thighs, head. Therefore, a technique that mitigates error caused by human is essential for future location-based service. If a person has a UWB wearable sensor, there will be large and small side errors depending on the sensor's position on the human body.[5] However, so far, research on mitigating errors in UWB indoor localization is focused on mitigating errors in indoor localization caused by NLOS effects of the indoor structure, and research on mitigating errors caused by human

body characteristics has not been well discussed. If content that utilizes high-precision indoor localization technology is increased, users who use that content will be primarily human. Also, content mainly will be provided content through the exact location of that person. To mitigate errors caused by the position of the UWB device on the human body during indoor localization, it is first necessary to know where the UWB device is on the human body. Therefore, we present a model that classifies where the UWB device located in the human body using convolutional neural network.

In this paper, we propose a framework considering the effect of human body in ranging error mitigating as depicted in Figure 1. The main contributions of the paper can be summarized as follows:

- Intelligently identify the position of the UWB device on the human body using convolutional neural network.
- Considering the position of UWB device on the human body, mitigate UWB ranging error.

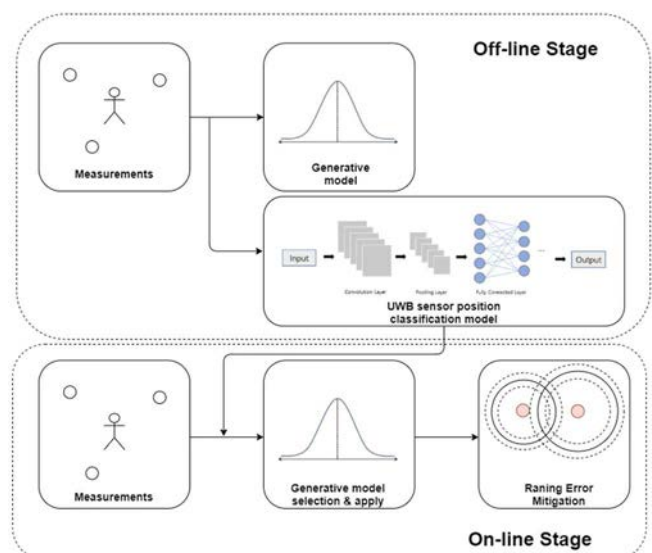


Figure 1. Proposed scheme for UWB ranging error mitigation considering the effect of the human body.

The remainder of the paper is organized as follows. Section II introduces our proposed scheme. Section III notify our experimental setup. Section IV presents the performance of ranging error mitigation considering the position of UWB device on human body. Finally, conclusions are given in Section V.

II. PROPOSED SCHEME

A. UWB Device Position Identifier

In order to classify the position of UWB device on the human body from the one-dimensional form of channel data, we used CNN structures. CNN consists of input, convolution layer, pooling layer, hidden layer, and output, as shown in Figure 2. In a convolution layer, features are extracted from the input with multiple kernel filters. After the feature extraction process takes place in the convolution layer, the down sampling process is operated in the pooling layer. A pooling layer minimizes training computation and time. Also, we used categorical cross entropy function as a loss function. categorical cross entropy function is mainly used to distinguish one class from a multiple class. Since the location of one of the five device positions must be identified in our proposed technique, categorical cross entropy function considered a loss function suitable for our proposed scheme.

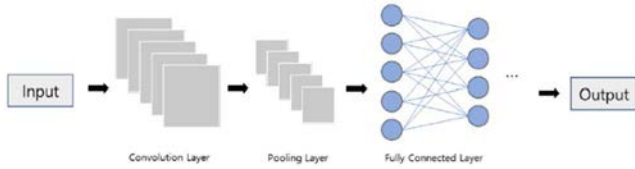


Figure 2. Neural Network structure: CNN

B. Ranging Error Mitigation Considering the Position of UWB Device on Human Body

In a general ranging error mitigation system, the two values in each collection of measurements $y = [r, \delta]$ are measurement distance(r) and NLOS indicator(δ). However, in our error mitigation system, the two values in each set of measurements $y = [r, \delta]$ are the measurement distance(r) and the position indicator of the UWB device on human body(δ). In particular, the distance measurement r is instantiation of

$$r = d + n \quad (1)$$

where d is distance between a UWB anchor and a UWB device and n is the measurement noise with PDF given by

$$f_n(n) = \begin{cases} \varphi(n; b_{tripod}, \sigma_{tripod}^2) & \text{for tripod case} \\ \varphi(n; b_x, \sigma_x^2) & \text{for a case on the human body} \end{cases} \quad (2)$$

$x = \{\text{hand, chest, thigh, fore-head}\}$

where b is a positive bias due to the position of UWB device. The other component, δ , of the measurement set is the UWB device position identifier outcome with $\delta = 0, 1, 2, 3$ and 4 corresponding tripod(not on the human body), hand, chest,

thigh and fore-head, respectively. The error in identifying the UWB position is accounted for by means of posterior probabilities of error

$$\epsilon_{tripod} = P\{tripod|\delta = 0\} \quad (3a)$$

$$\epsilon_{hand} = P\{hand|\delta = 1\} \quad (3b)$$

$$\epsilon_{hand} = P\{chest|\delta = 2\} \quad (3c)$$

$$\epsilon_{hand} = P\{thigh|\delta = 3\} \quad (3d)$$

$$\epsilon_{hand} = P\{fore-head|\delta = 4\} \quad (3e)$$

the distance ($\hat{d}$) after mitigating the error corresponding to measurements set $y = [r, \delta]$, described in (1)-(3)

$$\hat{d} = E(d|r, \delta) = \epsilon_y(r - b_y) \text{ for } \delta = 0, 1, 2, 3, 4$$

$$y = \{\text{tripod, hand, chest, thigh, fore-head}\} \quad (4)$$

The identifier output and its errors are considered independent of the distance. And identifier is highly reliable ($\epsilon_y \cong 1$). Therefore, the distance ($\hat{d}$) after mitigating the error is as follows:

$$\hat{d} = E(d|r, \delta) = r - b_y \text{ for } \delta = 0, 1, 2, 3, 4 \quad (5)$$

III. EXPERIMENTAL SETUP

We analyzed changes of CIR data depending on where the UWB device is located on the body with deep running and identified the location of UWB device on the body. To minimize other environmental impacts and analyze the effects of the body itself, we conducted the experiment at the first-floor lobby in campus building where is wide and unobstructed.

In this experiment, the position of the UWB device was divided into five categories (see Fig 3): (a) tripod, (b) hand, (c) chest, (d) thigh and (e) fore-head. (a) is a label to identify that the UWB device is not on the human body, and (b) through (e) is a label to identify that UWB device is on human body.

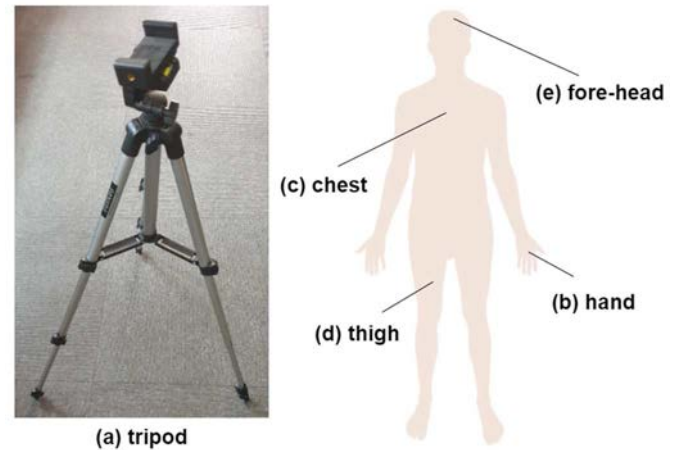


Figure 3. UWB device mounted on subject at (a) tripod, (b) hand, (c) chest, (d) thigh, and (e) fore-head

We collected 1500 data each for tripod, hand, chest, thigh, and fore-head label. During data collection we changed the position of the person with the device to diversify the environmental noise and distance. The collected data was randomly divided into train data, validation data and test data into 6:2:2.

The Decawave EVK1000 Evaluation Kit was used in UWB CIR data measurement. Collected UWB CIR data consists of 1016 real parts of signals and 1016 imaginary parts. Each pair of the real and imaginary signal is measured one in every nanosecond. The channel setting of the transceiver was the data rate of 110 kb/s, central frequency of 4.0 GHz, preamble length of 1024, pulse reception frequency of 64 MHz. Proposed NN models were implemented in Ubuntu 18.04 workstation with i9-7940x CPU (3.10GHz), 128G RAM, 2 GTX 1080Ti Sli GPUs and 1TB SSD.

CIR data is time-dependent because it is data from signal waves, and the number of features in one data is as large as the image. Therefore, we used CNN as a neural network structure (see Figure 2), and we optimized the neural network structure through repeated experiments for this experiment. The detailed network setups for CNN is shown in Table 1.

TABLE 1. NEURAL NETWORK LAYER CONFIGURATION INFORMATION OF CNN USED IN THE EXPERIMENT

Layer	Neural Network layer configuration information		
	Layer(type)	Shape	Parameters
Layer1	input (InputLayer)	2032	0
Layer2	reshape (Reshape)	(2032,1)	0
Layer3	conv1d (Conv1D)	(2024,8)	80
Layer4	max_pooling1d (MaxPooling1D)	(1012,8)	0
Layer5	conv1d_1 (Conv1D)	(1004,16)	1168
Layer6	max_pooling1d_1 (MaxPooling1D)	(502,16)	0
Layer7	conv1d_2 (Conv1D)	(494,32)	4640
Layer8	max_pooling1d_2 (MaxPooling1D)	(247,32)	0
Layer9	conv1d_3 (Conv1D)	(239,64)	18496
Layer10	max_pooling1d_3 (MaxPooling1D)	(119,64)	0
Layer11	conv1d_4 (Conv1D)	(111,128)	73856
Layer12	max_pooling1d_4 (MaxPooling1D)	(55,128)	0
Layer13	flatten (Flatten)	7040	0
Layer14	dense (Dense)	960	6759360
Layer15	dense_1 (Dense)	860	826460
Layer16	dense_2 (Dense)	560	482160
Layer17	dense_3 (Dense)	460	258060
Layer18	dense_4 (Dense)	360	165960
Layer19	dense_5 (Dense)	5	1805

In Table 2, we observe a clear relationship between the localization performance and the position of UWB device. Most of the errors observed are caused by body shadowing of UWB device by corresponding body position, i.e., chest, thigh, and head.

Overall, the biggest error occurred when the device was attached to the chest, followed by the degree of error in hand and leg order. In addition, the smallest error occurred in the case of the head.

TABLE 2. UWB RANGING ERROR TO UWB DEVICE POSITION: MEAN, STANDARD DEVIATION (IN M).

Indicator	UWB Device position				
	Tripod	Hand	Chest	Thigh	Fore-head
Mean	0.12	0.29	0.44	0.21	0.19
Standard deviation	0.04	0.32	0.71	0.27	0.16

IV. PERFORMANCE

Table 3 shows the position of the UWB device as predicted by the identifier for the actual location of the UWB device. Table 4 shows the identification accuracy of the identifier with the precision and recall values calculated based on Table 3. The identifier has a high accuracy of at least 93.7% to 100% for each UWB device location. Through these results, we consider that the identifier has sufficient performance to be used to mitigate range errors.

TABLE 3. IDENTIFICATION PERFORMANCE OF UWB DEVICE POSITION IDENTIFIER: PREDICTED LABEL & ACTUAL LABEL.

Predicted label	Actual label				
	Tripod	Hand	Chest	Thigh	Fore-head
Tripod	293	0	1	1	0
Hand	1	296	0	1	18
Chest	2	0	298	3	0
Thigh	0	0	0	286	0
Fore-head	4	4	1	9	282

TABLE 4. IDENTIFICATION PERFORMANCE OF UWB DEVICE POSITION IDENTIFIER: PRECISION & RECALL.

Indicator	UWB Device position				
	Tripod	Hand	Chest	Thigh	Fore-head
Precision	99.3%	93.7%	98.4%	100%	94%
Recall	97.6%	98.7%	99.3%	95.3%	94%

Table 5 shows MSE values for mitigating range errors while considering the effects of the human body and mitigation range errors without considering the effects of the human body. When the UWB device is on a tripod, the identifier can slightly mispredict that the UWB device is on the human body. As a result, the MSE value increased when the body effect was considered than when the body effect was not considered. But, when the UWB device is on the human body, the MSE value significantly decreased when the body effect was considered than when the body effect was not considered.

TABLE 5. MEAN SQUARE ERROR OF RANGING TO THE POSITION OF UWB DEVICE

Indicator	UWB Device position				
	Tripod	Hand	Chest	Thigh	Fore-head
Body effect not considered	0.0016	0.1317	0.6111	0.0843	0.0314
Body effect considered	0.0017	0.1015	0.5052	0.0755	0.0262

V. CONCLUSIONS

The field of indoor localization using UWB is highly useful in various industries due to its high-precision and robustness to obstacles. However, in these areas, the error caused by NLOS caused by inter-communication inter-terminal obstacles is the biggest problem that needs to be addressed by compensating for the errors caused by NLOS and increasing the measurement accuracy. Recently, various approaches to responding to errors have been attempted using deep learning, but this is mostly the study of NLOS by indoor obstacles, and there is not enough research to respond to NLOS by the human body. Therefore, we proposed a system to identify where the UWB device is on the body and apply range error mitigation differently depending on the location of the UWB device to mitigate errors caused by NLOS by the human body. As a result of the experiment, the UWB device location identifier showed the identification accuracy of 99.3%, 93.7%, 98.4%, 100%, and 94%, respectively, for tripod, hand, chest, thigh, and fore-head.

Also, our proposed schemes mitigated errors on hand, chest, thigh and fore-head by 22.93%, 17.32%, 10.4%, and 16.56%, respectively, compared to when the effects of human body were not considered. The following study attempts to mitigate localization error according to the position of the UWB device on the human body, not to mitigate the range error.

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REFERENCES

- [1] F. Alkhawaja, M. Jaradat, and L. Romdhane, "Techniques of indoor positioning systems (IPS): A survey," in 2019 Advances in Science and Engineering Technology International Conferences (ASET), 2019, pp. 1–8.
- [2] Q. Fan, B. Sun, Y. Sun, and X. Zhuang, "Performance enhancement of MEMS-based INS/UWB integration for indoor navigation applications," *IEEE Sens. J.*, vol. 17, no. 10, pp. 3116–3130, 2017.
- [3] B. Silva, Z. Pang, J. Akerberg, J. Neander, and G. Hancke, "Experimental study of UWB-based high precision localization for industrial applications," in 2014 IEEE International Conference on Ultra-WideBand (ICUWB), 2014, pp. 280–285.
- [4] S. K. Leem, F. Khan, and S. H. Cho, "Remote authentication using an ultra-wideband radio frequency transceiver," in 2020 IEEE 17th Annual Consumer Communications & Networking Conference (CCNC), 2020, pp. 1–8.
- [5] Otim, Timothy, et al. "Effects of the body wearable sensor position on the UWB localization accuracy." *Electronics* 8.11 (2019): 1351. J. Clerk Maxwell, *A Treatise on Electricity and Magnetism*, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68-73.



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