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## Research Article

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# UWB Indoor Localization in LOS and NLOS Situations based on Fingerprinting with Deep Learning

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## Abstract

As wireless communication technology develops, services using user's location information are also increasing and becoming important. Among many technologies that can measure position, ultra wideband (UWB) is being used in many fields of robot and human positioning systems. A high-precision technology using UWB can find targets with an error of a few centimeters, from industrial robot operations to drones used in search and rescue operations. In this paper, indoor positioning is performed using UWB boards in line of sight (LOS) and non line of sight (NLOS) situations. With the long short-term memory (LSTM) Deep Learning Algorithm, we propose a method for compensating location errors and predicting a more accurate location. In the LOS situation, the location was measured based on fingerprinting using four anchors and tags. The measured distance values were classified into training and test dataset. By applying these distance values to the LSTM, it was confirmed that the position error was compensated. In the NLOS situation, the quality factor was measured for each obstacle by placing four types of obstacles (no obstacles, metal, mirror, multipath) between the anchor and the tag at a distance of 4 meters. By applying the measured values to the LSTM, it was confirmed that the position error was compensated by detecting an abnormal signal occurring in the UWB board. Finally, the experimental results show that the proposed method can provide more accurate position compensation and prediction in LOS and NLOS environments.

**Keywords:** UWB (Ultra Wideband) Line of Sight (LOS) None Line of Sight (NLOS) Long Short Term Memory (LSTM) Quality Factor

# 1 Introduction

As wireless communication technology develops, services which is using user's location information are also increasing and becoming more important. There are several technologies that can measure location like GPS, UWB, Wifi, Bluetooth and Zigbee etc. Among them, UWB is used in location systems in many fields. A high-precision technology called UWB allows anything from industrial robotic operations to drones used in search and rescue operations to find targets with an error of a few centimeters [1]. Although UWB technology was introduced a few decades ago, it has recently been attracting attention again. In past, there was a limit to the data transmission speed, but recently the advantages of UWB have begun to be highlighted again as services focused on location determination have diversified [2]. In the future, when carrying heavy luggage through the ticket gates of the subway, turning on the computer and logging in for urgent work, these are all aspects of life that UWB technology will open [2]. In addition, a service that recommends the most popular products or products with the highest ratings in the current location based on the user's location information will be possible.

The purpose of this thesis is to perform indoor localization using Qorvo's UWB board in LOS and NLOS situations, and to compensate for location error and predict more accurate location by applying the location to the Deep Learning Algorithm. In the LOS situation, the location was measured based on fingerprinting to create training data set and test data set using 4 anchors and tag. And it was confirmed that the location error is compensated by applying it to the LSTM. In the NLOS situation, Received Signal Strength was measured by arranging obstacles such as mirrors and cooking foils between the anchor and the tag at 4M distance and configuring an environment in which multi-path occurs. And it was confirmed that the position error is compensated by visualizing the data of how much the difference in Quality Factor according to the obstacles occurred and applying this to the LSTM to detect the abnormal signal generated in the UWB board.

This paper consists of a total of five sections including the introduction. Section 1 explains the background of the thesis and the technology that can measure the position. UWB which has recently been attracting attention again will be introduced. Section 2 summarizes what UWB is and how it is used for localization. We will learn about LSTM which is a Deep Learning Algorithm and describe the differences from other algorithms. Section 3 describes the design and implementation. Learn about the UWB system used for distance positioning. Then the data to be applied to the LSTM is divided into training and test dataset by positioning in LOS and NLOS situations, then LSTM implementation method will be described. Section 4 deals with performance evaluation. The experimental environment for positioning in LOS and NLOS situations will be discussed, and performance evaluation will be discussed in LOS and LNOS. Finally, the conclusion is summarized in Section 5.

## 2 Related work

UWB was developed and used as a wireless communication technology for military use in the United States in 1970, and began to attract attention when it was opened to the civilian population [3]. And it received a lot of attention from 2000 to 2010, but it did not succeed because there was a lack of eco system compared to WIFI and there was no company leading the market [4]. However, the situation has changed since 2019 when Apple's iPhone 11 was equipped with UWB. It is not a new technology, but it started to provide various services to consumers as it was installed in the apple iPhone. After that, Samsung and other smartphone makers started to use UWB, but it was Apple that firstly introduced UWB and started providing location-related services to consumers. Apple is developing a digital car key-related service that uses the iPhone as a car key using UWB. And Samsung launched a Smart Tag that uses UWB and BLE to notify the location of an object. According to a recent survey, the technology using UWB is expected to grow by more than 20% per year, so it is necessary to further interest in and development of it. Figure 1 shows that fingerprinting method determines the area in a grid method and measures the signal strength which received from WIFI or Bluetooth at that location. The Fingerprinting technique is highly influenced by the surrounding environment because it estimates the location based on the signal strength. In addition, even if the signal at the same location is measured, the strength of the signal may be different each time.

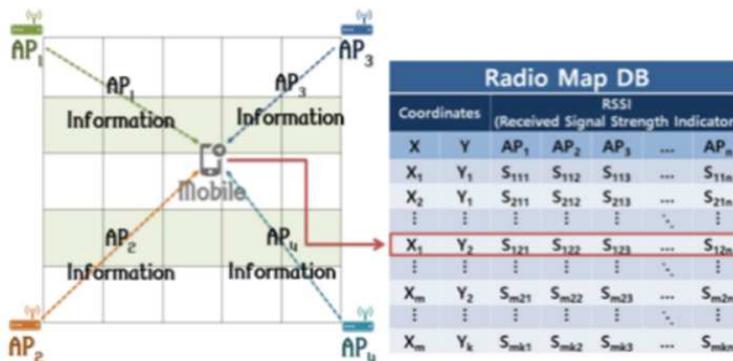
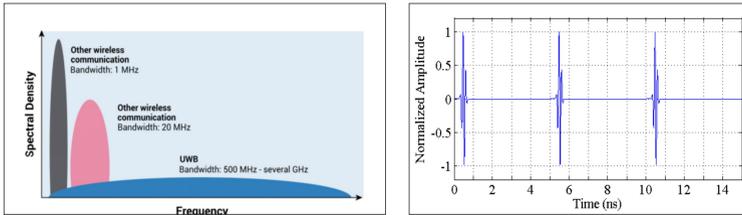


Fig. 1 Localization based on fingerprinting

UWB is a wireless communication technology that transmits a large amount of information with low power over a very wide band compared to the existing spectrum [3] as described in Figure 2. In addition, it has advantage for high-speed communication because it uses a high-power radio wave while using a wide bandwidth, and the pulse period is 2ns. Wireless communication technologies are classified according to wave reach. There is WPAN which has about 10m of radio wave reach, and WLAN which has about 100m of radio

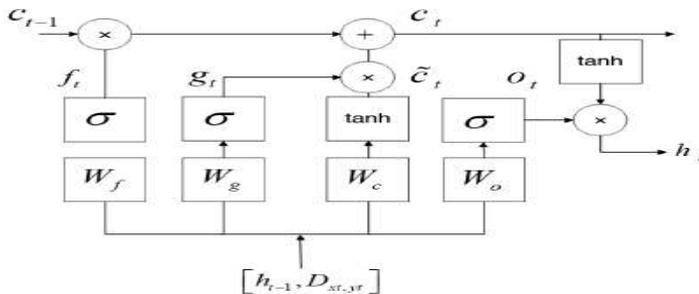
wave reach, and WWAN which has several tens of kilometers of radio wave reach. The radio wave reach of UWB is more than 100m based on LOS [5]. However, UWB belongs to WPAN because UWB technology was developed with the goal of transmitting radio waves of about 10m in past. UWB has been used as a military wireless communication technology by the US Department of Defense for over 40 years [3], and military security has been released and the IEEE has defined the UWB technology standard. The IEEE defined the name of UWB as 802.15.4a [4], and the technology which is applied to mobile phones is IEEE 802.15.4z.



**Fig. 2** UWB spectrum and pulse.

IEEE 802.15.4z complemented PHY and MAC of IEEE 802.15.4z which is a UWB standard, and added precision positioning and security related functions. The characteristics of UWB are low power consumption, strong resistance to radio wave interference, and high accuracy of position detection, so the error is within a few centimeters.

Recurrent Neural Network processes inputs and outputs in sequence units and is the most basic sequence model in deep learning. In RNN, the cell plays a role in sending the result through the activation function in the hidden layer. The memory cell of the hidden layer uses data from the memory cell of the previous time as its input. In this way, the state value sent by the memory cell at the previous point in time is used as an input value. A disadvantage of RNNs is the problem of cell long-term dependence. LSTM resolve the problem

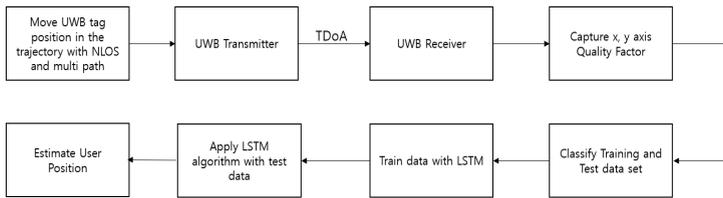


**Fig. 3** Propagation of long short term memory (LSTM).

of RNN cells which have long-term dependency problem and perform learning in a section requiring a long dependency period. LSTM Cell is divided into two vectors  $H(t)$  and  $C(t)$  as described in Figure 3.  $H(t)$  is called a short term state, and  $C(t)$  is called a long term state. In LSTM, the long-term memory  $C(t-1)$  passes from the left to the right of the cell, and some information is lost as it passes through the forget gate, and then a part of new memory is added from the input gate by addition (+) operation.  $C(t)$  created in this way is directly output without additional operation. And it is passed to the Hyperbolic Tangent( $\tanh$ )function of the output gate to create a short-term state and the cell of output.

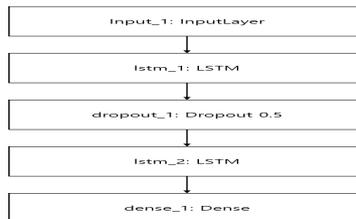
### 3 Design and Implementation

The overall UWB system stages using LSTM are summarized in Figure 4. The anchors positions are defined and UWB tag moved in the trajectory with NLOS and multi path and the overall UWB system is illustrated in Figure 4 as a block diagram.



**Fig. 4** Block diagram of overall UWB system.

Figure 5 shows that proposed LSTM system which is used for this paper. Localization was performed by putting the position data which measured using the UWB board as the input of the LSTM. It has different location data for learning in LOS and NLOS situations [6]. So, LSTM was implemented according to LOS and NLOS. Fig 5 shows that proposed system of the LSTM which implemented in NLOS situation. The hidden layer and epoch of LSTM are 500.



**Fig. 5** Model structure of proposed LSTM system.

In this paper, Qorvo's DWM1001 boards which satisfies IEEE 802.15.4 are used as a real-time positioning system. The DWM1001 integrates UWB and Bluetooth chips and has a motion sensor [7]. The main characteristic of DWM1001 is that the distance measurement error is less than 10cm and it uses a frequency band of 6.5GHz. And the data transmission speed is 6.8Mps, and distance measurement is possible up to 60m in LOS situation.



**Fig. 6** DWM1001 UWB board.

The system can be composed of anchors and tags using 12 DWM1001 boards as shown in Figure 6. Anchors can set up to 11 boards and tag can set up to 8 boards. In addition, the manufacturer provides a mobile application which is dedicated to UWB. We can check real-time location information measured from anchors and tags through the application. Also, real-time location information can be checked in csv format through putty. X, Y, Z coordinates and Q factor values can be checked as real-time location information when PC and UWB board are connected.

### 3.1 Classification of LOS and NLOS

In this paper, the positions of anchors and tags are arranged differently in LOS and NLOS situations as described in Figure 7. In the LOS situation, the anchors were arranged in a square shape and the location data was measured by dividing it into a training area and a test area using the fingerprinting method. We tried to secure reliable data by measuring 900 positions data as the training data set and 800 position data as the test data. In the NLOS situation, position data was measured by placing obstacles such as cooking foils and mirrors between the anchor and the tag. The location data was measured by configuring the environment where multipath occurs. A total of 5,133 location data were obtained and 2,200 samples were used as the training data set, and 100 samples were used as the test data to secure reliable data.

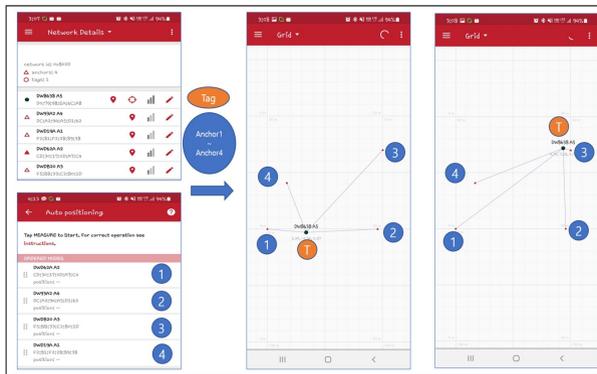


Fig. 7 Mobile application for UWB

## 4 Experiments and Performance Evaluation

This thesis proves that the abnormal signal which measured on the UWB board in LOS and NLOS situations is compensated after applied LSTM algorithm. To maximize the performance of the LSTM algorithm, performance analysis is performed according to the optimizer. The performance analysis according to the learning rate, batch size, and hidden layer of the LSTM used in this paper is shown in a graph.

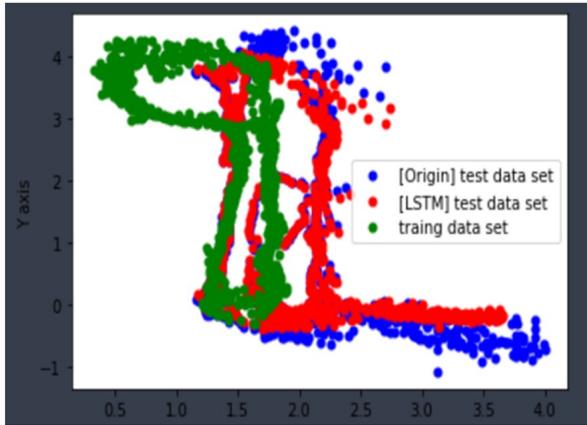
### 4.1 UWB LOS environment

In this paper, 4 Anchors are arranged in 3 meters X 3 meters in the living room in LOS situation. In order to evaluate the performance of LSTM, as shown in Figure 8, trajectory of the UWB tag was divided into two areas in the form of fingerprinting [8]. First, measurements were made while moving at least 10 times in a green trajectory as shown in the figure below to secure the training data set. And the test data set was secured by moving more than 10 times in the form of a blue trajectory. Distance information which received by UWB tag through 4 anchors is connected to PC and transmitted using UART interface.

### 4.2 UWB NLOS environment

In the NLOS situation, obstacles were placed between the anchor and the tag so that the direct path was not created. In addition, the anchor was placed in the room and the Tag was placed inside the living room to create a multipath. The distance between Anchor and Tag is 4 meters [9]. As shown in Figure 9, cooking foil and mirror were placed between anchor and tag to measure Quality Factor and use it as a training data set. In addition, Quality Factor was measured in an environment where multipath occurs in the room and living room and used as test data set. The UWB signal may be different depending on the environment of the room and living room [10], but this part was not considered in this paper.





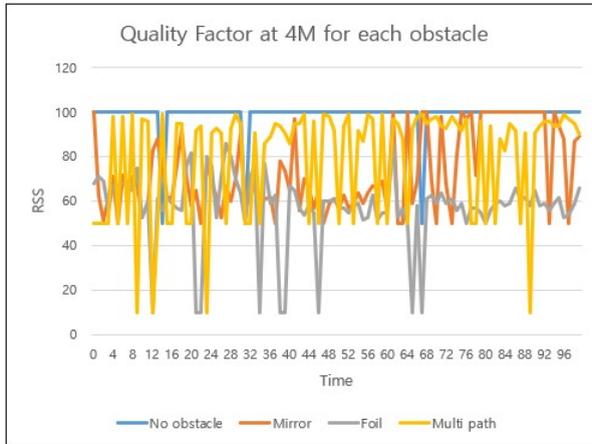
**Fig. 10** LSTM trajectory for training and test.



**Fig. 11** Average of quality factors and error rates.

Quality Factor was measured when there was no obstacle between Anchor and Tag, and it was confirmed that most  $QF = 100$  came out. Then, mirror and cooking foil were placed between the anchor and the tag to measure the QF. When the multipath of the room and living room occurred, the QF was measured to test how much loss occurred.

Figure 11 and Figure 12 show the quality factors for each obstacle measured in NLOS situation. Loss of about 42% compared to normal quality factor occurred in the cooking foil obstacle which has metallic properties and loss of about 26% compared to normal quality factor occurred in the mirror. In addition, about 20% of quality factor loss occurred in the room and living room where multipath occurred and it was used as test data.



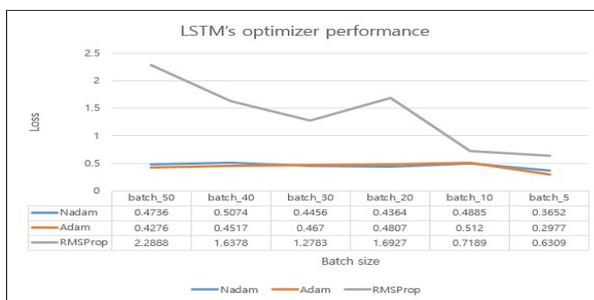
**Fig. 12** Quality factor for each obstacle at 4M.



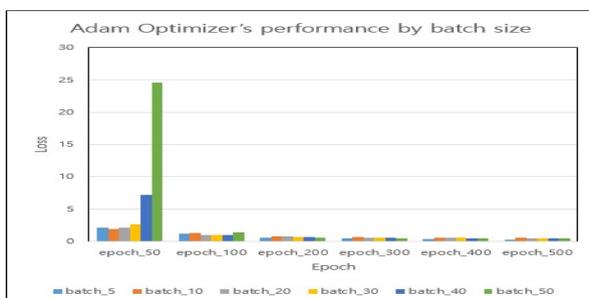
**Fig. 13** Compensation of quality factor with LSTM applied.

It was confirmed that the abnormal signal measured on the UWB board was filtered when LSTM was applied to the Cooking foil and multipath data. And it was confirmed that the cooking foil showed 6.748% of quality factor compensation effect and 2.93% of quality factor compensation effect in multipath environment.

Figure 14 shows the performance comparison according to the optimizer of the LSTM model. Adam and Nadam performed well but Adam was slightly better so I used Adam. And RMSProp relatively had a large loss when LSTM was applied and Adadelta had a loss of 250 or more, so it was excluded from the performance evaluation.

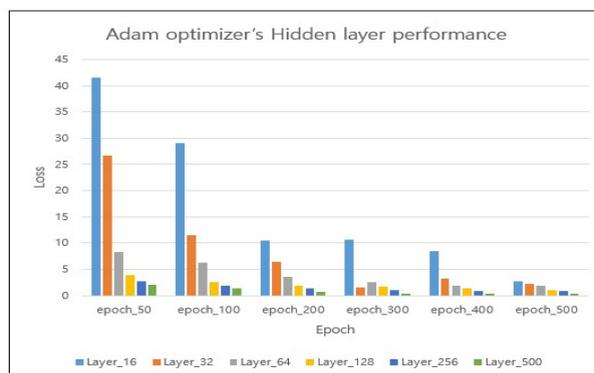


**Fig. 14** Comparison of performance according to the optimizers.



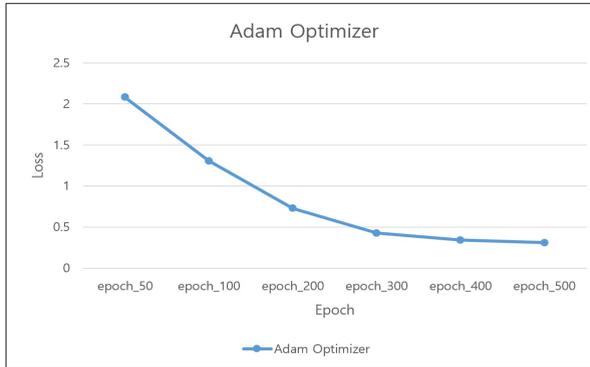
**Fig. 15** Comparison of performance according to the batch size.

Figure 15 shows performance comparison according to batch-size of Adam optimizer. The smaller the batch size, the better the performance. However it takes a long time to learn and if it is set too small, the possibility of overfitting increases. In NLOS situation, MSE loss = 0.2864 when epoch = 500 and batch-size = 5.



**Fig. 16** Performance comparison according to hidden layers.

Figure 16 shows the performance comparison according to the hidden layer of the Adam optimizer. The batch size is fixed at 5 and shows the best performance when set to Hidden layer = 500 and dropout (0.5).



**Fig. 17** Performance comparison according to the learning rate.

Figure 17 shows the performance comparison of the Adam optimizer according to the learning rate. It showed the best MSE loss when batch size = 5, hidden layer = 500, learning rate (epoch) is set to 500. In the case of LOS, overfitting occurred and the performance deteriorated when the learning rate was set to 200 or higher.

## 5 Conclusion

In this paper, UWB indoor positioning compensation system using the Deep Learning Algorithm method called LSTM is presented in LOS and NLOS situations. In the LOS situation, the distance information between the anchor and the tag is input as the input of the LSTM based on Fingerprinting, the user's exact location is predicted and if an abnormal location is found from UWB board, it will be possible to compensate for it. In the NLOS situation, we experimented based on Quality Factor data in an environment where metal, mirror, and multipath occur at a distance of 4M. By acquiring a total of 5,133 Quality Factor data samples, training data and test data were used to learn the LSTM, proving that position compensation can be performed in the most common NLOS environment in real life. After confirming that the user's location is accurately predicted with LSTM, hyperparameter tuning was performed to maximize LSTM performance in LOS and NLOS environments (Optimizer, Hidden Node, Batch-size). Through the experiments, it was verified that position compensation and more accurate position prediction are possible in LOS and NLOS environments when LSTM is applied.

## Declarations

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- **Conflict of interest:** The authors declare that they have no conflict of interest.
- **Ethics approval:** Not applicable
- **Consent to participate:** Not applicable
- **Consent for publication:** Not applicable
- **Availability of data and materials:** The data that support the findings of this study are available on request from the corresponding author, I. J. The data are not publicly available due to their containing information that could compromise the privacy of research participants.
- **Code availability:** The data for this project are confidential, but may be obtained with Data Use Agreements with the Computer Software Department of Hanyang University. Researchers interested in access to the data may contact Heejae Kim at im60212@naver.com. It can take some months to negotiate data use agreements and gain access to the data. The author will assist with any reasonable replication attempts for two years following publication.

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