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Deep Learning based Non-Line-of-Sight Identification with Sub-1GHz Narrow Band Frequency

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Abstract

Identifying Non-Line-of-Sight (NLOS) conditions has brought new phenomena for indoor localization. NLOS Identification has increased the accuracy of indoor localization by either combining the PDR (Pedestrian Dead Reckoning) system with RSSI (Received Signal Strength Identification) or combining Wireless transmission based indoor localization with RSSI. Identifying NLOS condition techniques has been primarily investigated for wireless transmissions such as Ultra-Wide Band (UWB) and Wi-Fi transmissions. Nevertheless, in cases of emergency situations such as fire break out and power failure, these infrastructures are hard to be fully utilized. Moreover, the distance the signal can travel for UWB transmission is 5-10m and Wi-Fi transmission are able to travel up to 50m indoors. In this paper, we introduce a new and efficient methodology for indoor localization where there is no pre-installed infrastructure help such as emergency situations. We introduce the use of sub-1GHz wireless transmission for indoor localization. The sub-1Ghz are able to reach up to 200m indoors, and like other wireless transmission, to increase the accuracy of localization we have implemented NLOS identification on sub-1GHz wireless transmission. We have used deep learning for NLOS identification by measuring RSSI and using this dataset for deep neural network classification and was able to achieve 92.58 accuracy of NLOS identification. This proposed method will help enhance indoor localization during emergency situations and benefit from longer distance signal transmission.

Keywords: NLOS Identification, Deep Learning, Deep Neural Network, Indoor Localization, Internet of Things

I. INTRODUCTION

Indoor localization has become an arising issue for smart city, smart factory and smart home applications. In detail, indoor localization systems are applied to industrial applications such as location-based commerce, equipment or robot tracking and for emergency situations such as tracking firefighters inside the building. Ways to conduct indoor localization and to increase the accuracy of indoor localization, many researches have been conducted on several kinds of fields such as PDR system and wireless transmission fields. A PDR system is one of the fields that has been conducted recently for identifying locations of firefighter inside a building. PDR system uses an IMU (Inertial Measurement Unit) system which includes Gyro, Magnitude, and Accelerator sensors to predict and track one's motion and position inside the building. Continuously, indoor localization using wireless transmission, the radio frequency signal strength, such as RSS (Received Signal Strength) are being utilized. These signal values are collec

ted from UWB (Ultra-wide band) and Wi-Fi transmission and are used to estimate the distance between the transmitter and the receiver. Especially, researches using UWB transmission was able achieve high accuracies. The algorithm proposed in [2] was able to achieve an accuracy of average distance error of 9.2cm and the algorithm proposed in [3] was able to obtain accuracy of average distance error of 2.5cm.

However, UWB signal has a critical disadvantage which is that UWB signals can only be transmitted for a range of 5-10m. In addition, because of its short-range transmission and the unique equipment it requires, constructing the UWB infrastructure inside a building requires expensive cost. The implementation of several specialized equipment for every 10m around the building will be costly and inefficient. Therefore, researches on Wi-Fi based approaches has started to gain attention from researchers.

Different from UWB based, Wi-Fi based approach has the advantage of the use of commonly existing Wi-Fi infrastructure inside buildings. In addition, Wi-Fi has a longer transmission distance range, bringing reduction to equipment requirement for indoor localization system implementation inside a building. Wi-Fi transmissions can typically transmit up to 50m indoors while UWB signals only reach up to only 5-10m which gives a huge advantage. However, using Wi-Fi RSS data to predict the distance between the transmitter and the receiver gets more complicated. Since the Wi-Fi signal can easily travel through walls and obstacles it becomes hard to identify the right distance. The RSS will attenuate significantly as the signal travel through obstacles unlike UWB signals which cannot propagate throw more than one obstacle. Using the attenuated RSS data can cause large distance error for indoor localization. For example, in a LOS condition, with 10m distance from transmitter to receiver, the RSS was measure as -70dBm but in NLOS condition with same distance RSS is measured as -75dBm or less. To resolve this problem researchers conducted a research on identifying the LOS or NLOS environment before they decide to distance of the transmitter and the receiver. Therefore, identifying LOS condition or NLOS condition has become another research field. Through these researches, indoor localization has become possible to estimate one's position with less distance error with Wi-Fi transmission.

Wi-Fi based Indoor localization is cost efficient and is easier to implement globally. However, to estimate exact indoor location with small distance error, there still exists of few issues involving the LOS and NLOS identification from above. For accurate distance measurement Wi-Fi APs are needed for each 1m. The signal transmission range of Wi-Fi is still not enough to cover a whole building and to estimate an accurate indoor location more than hundreds of APs are necessary. Also, in case of emergencies, utilizing the Wi-Fi infrastructure will not be available since Wi-Fi equipment are hard to be alive in situations such as blackouts and a fire break out. In this paper, we propose the use of sub-1GHz band for indoor localization designed with IoT devices and will propose a method to identify LOS or NLOS condition with our chosen feature through the experiment we have conducted. For the experiment, we have collected RSS dataset and extracted features to train deep neural network classification model. The features will help distinguish whether the signal is transmitted from a LOS or NLOS environment.

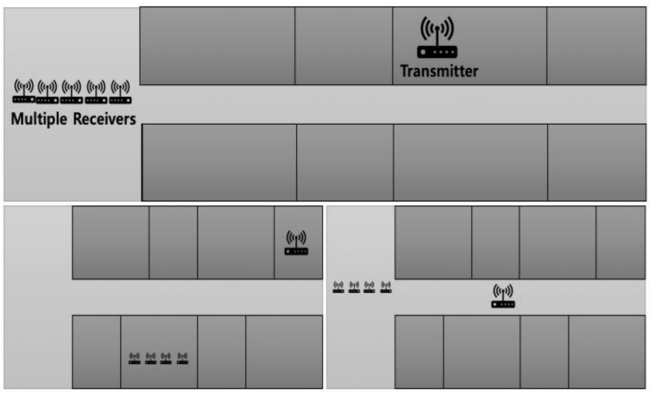

Figure 1. Data Collected in Various LOS/NLOS Condition

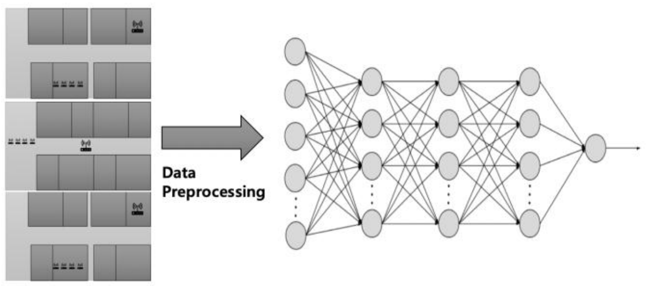

Figure 2. RSS based NLOS Identification Framework

The remaining sections details on the description of the proposed idea of using sub-1GHz transmission for indoor localization. Section 2 introduces related works to this paper research. Then Section 3 will explain about the proposed framework with how data was collected and how feature extraction was done. Section 4 explains the evaluated method and the accuracy of NLOS identification model. We have designed three difference models of deep neural network to test out the result and build our indoor localization system. Finally, Section 5 gives a conclusion to this paper.

II. RELATED WORK

Now, most of the researches have moved on to Wi-Fi based indoor localization from UWB based indoor localization for more efficiency. UWB based method was able to achieve average distance error of 2.5cm [2]. However, because the need of special equipment researchers has move on to utilizing Wi-Fi transmissions for indoor localization. Wi-Fi based approaches had some issues of signal travel through walls which caused significant distance error on the output. To minimize distance error caused by this issue, researchers utilized an additional information from NIC (Network Interface Cards) which contains the CSI (channel state information). The CSI is utilized to identify whether the signal in sent from a LOS or NLOS condition. The channel conditions are applied as an additional feature which is applicated by the IEEE 802.11 standard. For instance, the features selected from NIC measures are the depicting amplitudes and phases of every subcarrier explained in [4]. Another way for how the NIC measures is used is the collection of skewness of dominant path power and the kurtosis of frequency diversity variation proposed in [5]. This feature focus on different time-varying characteristics of each channel condition. Lastly, the variation in phase extracted from CSI [6] data are collected to be utilized. This variation in phase is applied in stationary situation where the number of multi-path components remains unchanged during sequential transmissions.

Table 1. CC1120′s wireless communication setting values

Frequency	433MHz
Tx Power	10dBm
Bit Rate	1.2kbps ~ 2.5kbps
Indoor Range	~200m

Other than utilizing the NIC, which requires specific LAN cards, machine learning approaches to identify LOS and NLOS conditions in Wi-Fi based indoor localization has been conducted. Machine learning approaches analyzed the characteristics of the RSS in LOS and NLOS to improve the accuracy of indoor localization. The training data sets were processed by conducting feature extract method from the RSS data collected. Features are preprocessed by applying mean, standard deviation, kurtosis, skewness, Rician K factor, and goodness of fit, etc. [7]. The algorithm used in other researches are LS-SVM (Least Square Support Vector Machine Classifier), GPC (Gaussian Processes Classifier), and HTC (Hypothesis Testing Classifier). The result from these machine learning algorithms gave a quite promising result of achieving 90% accuracy in NLOS identification.

III. PROPOSED NLOS IDENTIFICATION

A. Proposed Framework

RSS data was collected from various LOS and NLOS conditions. Examples on how the data were collected is shown in Figure 1. The IoT devices selected to measure RSS data are the CC1120 and STMF103C8 device. The CC1120 device is a fully integrated single-chip radio transceiver originally designed for high performance at low-power operation in cost-effective wireless systems. The device is mainly intended for Industrial, Scientific, and Medical (ISM) applications frequency bands at 164 to 192MHz, 274 to 320MHz, 410 to 480MHz, and 820 to 960MHz. The configuration CC1120 for our experiment is written in Table1. How RSS data were collected will be introduced in Section B. After RSS data are collected, data are passed through feature extraction stage to preprocess data before training the DNN model as shown in Figure 2. How data are rendered will be explained in Section C in detail. Then the extracted features will be feed into three differently layered deep neural network for evaluation and select the best NLOS identification model. For evaluation, testing data set are collected real-time and are preprocessed through the same method

Table 2. Average RSS measurement in LOS condition

Receiver1	Receiver2	Receiver3	Receiver4	Receiver5
-64.9	-65	-68.6	-60.1	-67

Table 3. Dataset Information

Dataset	Training set	Testing set	τ
DS-1	700	300	10
DS-2	700	300	20

Table 4. Deep Neural Network Structure

DNN	H-Layer 1	H-Layer 2	H-Layer 3	O-Layer
3-cls	256	256	-	1
4-cls	30	30	30	1
4.2-cls	100	100	100	1

above and feed into the model to estimate one's location minimizing the mean distance error of indoor localization.

B. Data Collection Method

For our experiment we have used multiple receivers to collect data, assuming there'll be difference in RSS values caused by multipath fading such as reflection, diffraction and attenuation. Since the measurement is done inside a building, there is a high chance of multipath fading especially when there's an obstacle between a transmitter and a receiver. This means that the difference of RSS between multiple receivers will maximize in NLOS condition. We used this characteristic to determine if the signal is being received from LOS or NLOS condition. Data are collected using five multiple receivers from one transmitter.

A transmitter transmits data for every 1 second and the multiple receivers each measures the RSS. This measurement was done in various LOS and NLOS condition inside our university building.

C. Data preprocessing

With the RSS measurement from multiple receivers, they are firstly normalized through the equation (1).

$$\varepsilon_j = RSS^i_{measured} - RSS^i_{\mu ean} \tag{1}$$

$RSS^i_{\mu ean}$ is the mean RSS value of receiver i measured from 1M distance in LOS condition. Each device sensitivity to each signal are different. An example is shown in Table 2. Each data was measured with a distance of 1M from the same transmitter to each receiver at a same location with the same condition. Within the same condition each device output a different value. Consequently, from this result, data normalization was needed to compare data with other receivers. After this normalization process, we have applied equation (2) to calculated how the signal changed within τ seconds.

$$\nabla = \varepsilon_j - \frac{\sum_{k\,=\,j-\frac{\tau}{2}}^{j+\frac{\tau}{2}} \varepsilon_k}{\tau} \tag{2}$$

With the average of consequent τ data relative to ε_j, the average

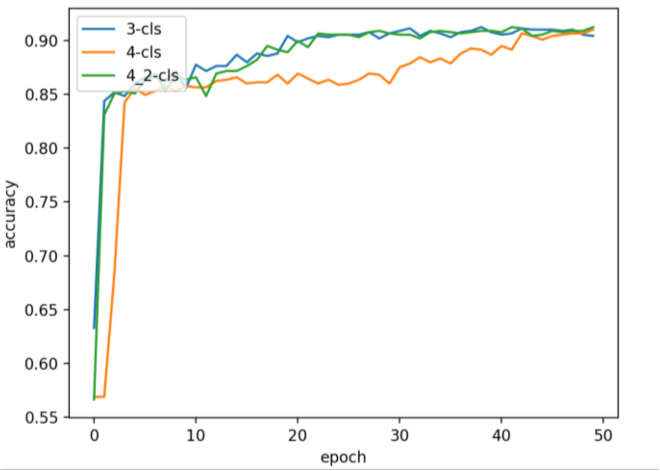

Figure 3. Evaluation of 3 Different DNN

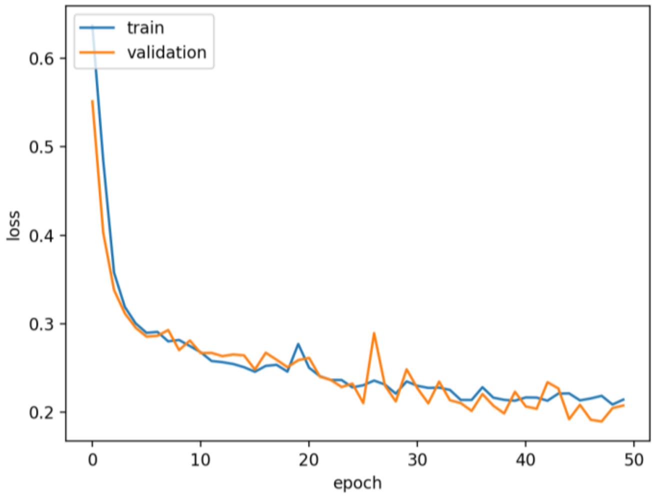

Figure 4. Model Loss

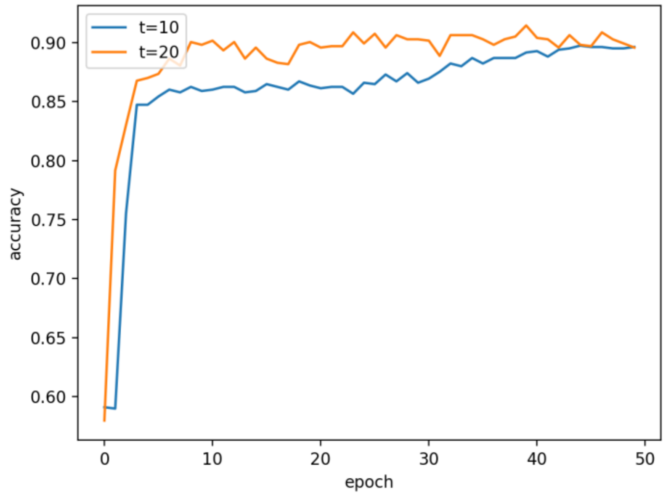

Figure 5. Different Time Intervals

RSS is calculated. After calculating the average, the deviation value is obtained through the summation of ε_j and the average. This equation is used to measure multipath fading of each receiver.

Finally, after applying these equations each data was labeled as either LOS or NLOS. This labeled dataset is for the latter deep learning classification.

D. Deep Learning Approach

To train the DNN classification model, data were collected as shown in Table 3. The difference between DS-1 and DS-2 is on how many data were used to calculate the average of the equation 2. To maximize the performance larger τ is required. However, larger τ means, to estimate whether the signal is received from LOS or NLOS, it needs τ samples for each measurement. τ samples are collected in τ second so larger τ means longer time it'll take to measure. Lastly, we have designed three different layered DNN to test out our experiment. How we structured the layers are shown in Table4.

IV. EXPERIMENT EVALUATION

A. Different layered deep neural network

Our experiment is conducted using three different layer deep neural network as shown in Table 4. All three networks are a classification model that classify LOS or NLOS condition. The first neural network contains three layers of one output layer and two hidden layers consisting 256 hidden nodes for each layer. The second and third neural network are similar consisting of four layers, but with different number of hidden nodes in the hidden layer. Figure 3 shows the evaluation on these three deep neural networks. It shows that the first and the third model are giving the best result for NLOS identification. From this experiment, we were able to determine how many layers and number of hidden nodes we'll be applying for future experiments. For further researches used the third model to evaluation other measurements.

B. NLOS Identification with Deep learning

With the fitted neural network architecture selected from above, we have validated our model with validation dataset that we have collected and left out for the validation of our model. With this validation set we have evaluated our model and was able to achieve an accuracy of 92.58 for identifying NLOS condition. The loss rate for each epoch is shown on Figure 4. As shown in Figure 4. we were able to analyze how the loss rate gradually decreases as the number of epochs increased throughout the training stage. This result has proven that the features we have selected was able to identify NLOS conditions inside a building.

C. Different τ selection

The selection of τ which can be addressed as time interval causes a significant effect on the accuracy of NLOS identification. We have tested out with two different types of time interval as shown in Table 3. The time interval we have selected are τ: 10 and τ: 20 and the result is shown in Figure 5. From this experiment, we were able to confirm that the selection of time interval highly effected the accuracy of NLOS identification. With the time interval of τ: 10 the accuracy we were able to obtain was 89.87. On the other hand, the accuracy for τ: 20 was 93.17. With this result we were able to verify that as the time interval increases the accuracy had also increased.

V. CONCLUSION

We have proposed a new method to identify NLOS condition. With the use of Sub-1GHz transceivers and by utilizing multiple receivers for RSS measurement, our research is distinct from others which are mostly based on UWB or Wi-Fi transmission. To maximize the accuracy using Sub-1GHz transmission, we have trained our DNN with preprocessed dataset. Through multiple receivers and data preprocessing we were able to achieve 92.58 accuracy of NLOS identification. Evaluation on our model was done with three different layered DNNs to find the best model. Continuously, we have experimented with two different time intervals ($\boldsymbol{\tau}$) which is used for preprocessing RSS data. The selection of longer time interval had increased the accuracy for indoor localization. Suggestions are made that the time interval should be chosen according to the surrounding real-time situation since the longer the time interval is, the model will not be able to estimate one's location in real time. However, as time interval is longer, higher the accuracy of NLOS detection is achieved. Also, there were some challenges that we have confronted during this experiment. The challenges that we have confronted were that the RSS values are highly variant to moving obstacles in between or around the transmitter and the receiver nodes. The RSS value was not able to give a constant value whenever there was a moving obstacle around. We suggest that this dilemma should be resolved in future works by utilizing semi-supervised learning in real-time or a need for moving obstacle detection algorithm. In future works, we will apply this NLOS identification to indoor location estimation and evaluate how the mean distance error is captured.

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