Improving TDoA based Positioning Accuracy using Machine Learning in a LoRaWAN Environment

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***Abstract*—LoRa is one of the low power wide area communication technologies (LPWA) that enables low cost chip module design due to low power, high receiver sensitivity and license-exempt bandwidth. Because of this, It is a technology suitable for IoT services with low data throughput and variability. For low-power-based positioning in LoRa environments While various techniques have been tried, The error is It is over a hundred meters. Because of this It is difficult to commercialize practical location services. In this paper, To reduce the TDoA positioning error, a train was made to correct the time error that occurs when transmitting. We propose a method of learning the time error in the DNN model and correcting it using the learned model in actual positioning. The experimental environment was constructed using python and keras. Experiment result, We confirmed that the error range decreases when the number of reference nodes and collected data are large and the mobile node is close to the reference node.**

***Index Terms*—LPWA, TDoA, LoRaWAN, location positioning, Deep Learning**

I. Introduction

LoRaWAN(Long Range Wide Area Network) is one of LPWA(Low Power Wide Area) technologies, and has low power, low cost and long distance communication. Devices used in LoRaWAN have high battery performance with output power not exceeding 10-25 mW according to the ISM(Industrial Scientic and Medical) frequency usage regulations. The communication distance is 2-15km from the city center and 30km from the area where the visibility is secured. It is characterized by low-cost construction because it uses the license-exempt band. [8]

There are many services based on location information in IoT service, such as wearable, machine control, safety monitoring, goods transportation and detection. [18] In the LoRaWAN environment, a GNSS(Global Navigation Satellite System) is generally used for precise location positioning. However, a commonly used GPS(Global Positioning System) receiver consumes additional power. [1] Since low power design is important in LPWA environment, it is necessary to study the positioning method instead of GNSS method.

Currently, various methods are being tried for low-power-based precise positioning in LoRaWAN. [2] LoRaWAN In the case of RSSI proximity method, an error of 1000-2000m occurred and an error of 300m or more occurs when TDoA is used . [3] Fingerprint Localization also has an average position error of 398.4 m. [5] The LoRaWAN RSSI proximity method is more error than fingerprinting or TDoA, and the fingerprinting method is difficult to implement in all LoRaWAN environments because the gateway is expensive.

In this paper, we have conducted research to reduce TDoA - based positioning error using deep learning. The positioning error of the TDoA is basically caused by a time error when transmitting and receiving signals between a BS(Base Station) and an MS(mobile station). We propose a method to calibrate this time error through a neural network. First, the reference node is installed in the coordinates determined in the LoRa environment. The server then collects time error data from the reference node. The collected error data is the time at which each of the three or more gateways arrives from the reference node installed at the determined coordinates. And Deep Neural Networks (DNN) learns the time it takes to reach it and the ideal reach time it takes from the reference node. We predict this ideal reach time as a model before positioning the mobile node to TDoA when going to the future operation stage. And estimates the position using the TDoA algorithm using the predicted arrival time.

II. Background

A. LoRa Network Architecture

LoRa is a technology developed to provide a longer range than traditional communication technologies. LoRa greatly improves receiver sensitivity and broadcasts the signal using the full channel bandwidth. [6] LoRa is the physical layer and LoRaWAN is the MAC protocol standardized by LoRa-Alliance. [7] LoRa Network is a ”star of stars topology” structure. There are basically three components in this Architecture. End-Device, Gateway, Network Server. [8]. They operate in the LoRa Network as follows. First, The End-Device communicates with the gateway using the LoRa protocol. The gateway receives the LoRaWAN Frame Packet from all end-devices included in the area and delivers it to the LoRa Network Server. However, the gateway can handle high traffic because it performs IP-based communication. The gateway is simply a packet forwarder. The LoRa Network Server

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interprets the LoRaWAN frame packet arriving from the End-Device.

The LoRa Gateway simply forwards the packets received from the End-Device and forwards the response from the Server to the End-Device. [9] Gateway is not connected to the end-device and receives all the end-device's packets included in the area in the LoRa protocol. [9] Also, as in Figure **??** , the gateway belongs to one LoRa Network Server. The location of this Gateway in LoRa Network Architecture enables its role as a Base Station for TDoA positioning.

The LoRa Network Server receives all broadcasted uplink packets from the End-Device. Therefore, it is important to design the network to keep the load low. The Network Server responds only to one of the same packets received from all the Gateways. Because of this structure, it is possible to collect multiple ToA data for one End-Device from each gateway. Therefore, it is possible to determine the position using the TDoA algorithm in the Server Layer.

B. Time Difference of Arrival

TDoA(Time Difference of Arrival) is a technique for positioning a mobile station using three or more base stations with precise time synchronization. [1] Sends the signal from the Mobile Station and obtains the relative time difference to each reached the Base Station. and a curve having the same time difference between the base stations is generated, and the position is obtained by triangulation.

1) Measure values in pairs of two spatially separated objects.
2) The position of the target is searched using the measured TDoA values and the location of the gateway which is known in advance.

The calculation for TDoA is as follows. The arrival distance is calculated by the arrival time at the gateway, and the simultaneous equations obtained here are calculated. The following is the calculation procedure of the TDoA algorithm. First, we measure the arrival time from the mobile node to the base station, and call it T_x. when c = luminous flux, The distance to the base station is (1). The coordinates of each base station is (x_1, y_1), (x_2, y_2), (x_3, y_3). and find the position (x_m, y_m) of Mobile Station using (2), (3)

$$D_1 = T_1 \times c \tag{1}$$

$$D_1 - D_3 = \sqrt{(x_1 - x_m)^2 + (y_1 - y_m)^2} - \sqrt{(x_3 - x_m)^2 + (y_3 - y_m)^2} \tag{2}$$

$$D_1 - D_2 = \sqrt{(x_1 - x_m)^2 + (y_1 - y_m)^2} - \sqrt{(x_2 - x_m)^2 + (y_2 - y_m)^2} \tag{3}$$

III. Related work

A. TDoA in LoRaWAN

TDoA is a method of estimating the position by triangulation by generating a time difference curve of a signal from a mobile station to three or more base stations. In LoRaWAN, the gateway becomes the base station and the end-device becomes the mobile station. Figure 1 is a way to find its intersection through two hyperbolas from three or more gateways. Much research has been attempted in LoRaWAN since TDoA-based positioning does not require a person to collect a database and does not require additional gateway costs.

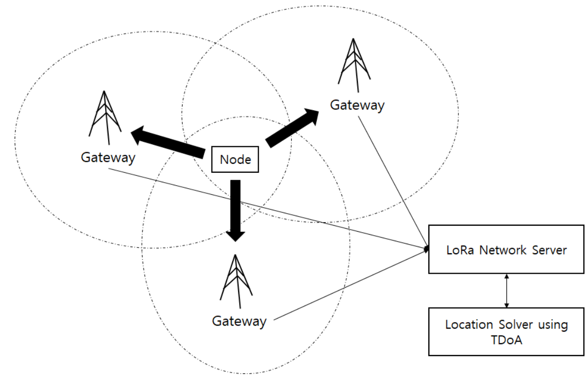

Fig. 1. Location Positioning using TDoA Algorithm in LoRaWAN

In fact, TDoA-based position location experiments were tested using the SX1272 chip, which supports LoRa communication. In this study, TDoA positioning was proved possible using LoRaWAN even though positioning error of more than 300m occurred. After that, according to an experiment in Eindhoven of the Netherlands, an average error of 480m occurred. Using the proposed tracking algorithm, we could reduce the mean error to less than 180m. However, this algorithm is an algorithm considering road map and moving speed. This is not applicable to all environments. [16]

In LoRaWAN, there is an advantage that data is received stably, but time error may occur from end-device to gateway. It is necessary to study the method of correcting the result after the positioning using TDoA.

IV. TDoA Positioning Correction Method Using Time Error Data Collection and Learning

We designed a Deep Nerual Networks model consisting of three hidden layers. This model continuously learns the packet arrival time between the reference node and the gateway. And corrects the arrival time of the Mobile Node in the operation phase. Reference Node and Mobile Node are End-Device. The Reference Node is an end-device that is installed at a predetermined coordinate to collect data. This serves to collect time errors to solve TDoA problems. The mobile node is a client device for which coordinate values have not been determined and actual positioning is required.

The positioning error of the mobile node is an error caused by the transmission delay. Because the cause of the Reference Node is the same, it is assumed that the cause of the position error of the two nodes is the same. Therefore, it is possible to correct the time error of the mobile node by using the model that trains the arrival time data through the reference node. Also, since the propagation environment may be different for

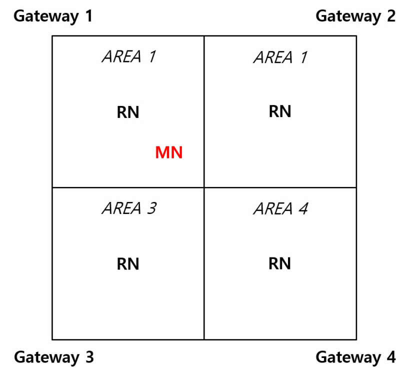

Fig. 2. 4 Reference Node

TABLE I
MAIN NOTATIONS

Symbol	Definition
$T_r g$	Time of Arrival from Reference Node to Gateway
$T_s rg$	Theoretical Time of Arrival from Reference Node to Gateway
$\Delta T_r g$	$T_r g - T_s rg$
$T_r g$	Time of Arrival from Mobile Node to Gateway
$\Delta T_m g$	$T_m g - T_s mg$ predicted using neural networks model
$T_s mg$	corrected arrival time from Mobile Node to Gateway

each area in a real environment, a reference node is installed in each area to collect data.

Figure 2 is a diagram showing the locations of Gateway, Reference Node, and Mobile Node for dividing into four areas within the gateway and performing the proposed experiment. The server collects the arrival times of the gateways from each reference node that reflects the time error. Designed Neural Networks learns this data and the actual time of arrival. The actual arrival time is the arrival time calculated using the specified coordinates. Using the arrival time of each gateway arriving from the Mobile Node, the server receives the corrected arrival time from Neural Networks. The position is estimated by the TDoA algorithm using the corrected arrival time. In this paper, it is assumed that the proposed system is divided into learning stage and operation stage. The following are variables and operation methods used to utilize the proposed system.

The method to correct the time error using the model is as follows. The following is the training phase.

1) Measure the value in pairs of two spatially separated objects.
2) Find the location of the target using the measured TDoA values and the location of the previously known gateway.
3) Sends a signal from the Reference Node to the gateway.
4) Stores the time taken from the Reference Node to each gateway ($T_r g$)
5) Obtain the theoretical time ($T_s rg$) from the reference node to each gateway using the TDoA algorithm.
6) Stores the difference between the time taken from the Reference Node to the gateway and the theoretical time (4).
7) Train $\Delta T_r g$ and $T_r g$ on the designed DNN model.

$$\Delta T_r g = T_r g - T_s rg \tag{4}$$

The operation steps are as follows.

1) The Mobile Node sends a signal to the gateway.
2) Stores the time taken from the Mobile Node to each gateway ($T_m g$)
3) Using $T_m g$ on the trained neural networks model predicts $\Delta T_m g$.
4) Combine $\Delta T_m g$ and $T_m g$. This is the theoretical time to arrive (5).
5) Calculate coordinates (X_m, Y_m) of Mobile Node with TDoA algorithm.

$$T_s mg = \Delta T_m g + T_m g \tag{5}$$

Since $T_s rg$ represents the actual arrival time from the reference node to the gateway, the location of the correct reference node is calculated by positioning using TDoA with $T_s rg$. That is, if you know $T_s mg$, it is possible to locate Mobile Node accurately. To do this, $DeltaT_m g$ was estimated from the neural network model and TDoA positioning was performed using the predicted $T_s mg$ to obtain corrected positioning values.

V. EXPERIMENT

A. Experimental method

In this paper, simulation environment is constructed by using simpy module of python. The propagation loss model considers only the environmental losses that vary over time using the Hata model. [17]. In addition, four gateways and four reference nodes were used, and the positions of the gateways and the reference nodes were fixed to predetermined coordinates. The distance between each gateway is 6Km and the total area is 36Km like Figure. 2.

B. Experiment of error rate measurement with and without training model

In this section, an experiment was conducted to find the error rate of neural networks with and without training. In the training phase, we trained 2500 data from each reference node and trained on the model. In the operation phase, we measured the error after receiving the arrival time 100 times from the mobile node.

Experimental results show that the error is greatly reduced when $\Delta T_m g$ is corrected by the model. The mean error was measured as 61m and the corrected error rate was reduced by more than 50%. The DataSet was collected 2500 times from all the Reference Nodes. The model was also trained over 1000 batch sizes and 10000 epochs

VI. CONCLUSION

Generally, the positioning error in the LoRa environment exceeds several hundred meters. In this paper, we have trained the time error using neural networks in training phase, and proposed a method to calibrate using neural network in operation phase. Experiments have shown that if the number and

TABLE II
MEASUREMENT OF AVERAGE ERROR VALUE WITH DNN MODEL VS. WITHOUT REFERENCE NODES

	without DNN model	with DNN model
error value	239.224m	61m

position of reference nodes are appropriate, proper positioning is possible with low cost and low power. In addition, the difference of correction according to presence or absence of neural networks exceeded 50%. However, when only one reference node was trained, the error was rather high. And the positioning error is still higher than the GNSS method, and the experimental environment is based on simulation. In the actual environment, various interferences are dependent on the region, so it is necessary to consider the location of the reference node. To do this, we need to study and test the proposed Prediction Model in real environment.

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