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DeepTAL: Deep Learning for TDOA-Based Asynchronous Localization Security With Measurement Error and Missing Data

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ABSTRACT The demand for accurate localization in complex environments continues to increase despite the difficulty in extracting positional information from measurements are not yet complete. Like any other process, localization also has security requirements. The use of ultra-wideband (UWB) indoor localization systems have recently grown quickly in industries, with a reliable, fast, and have high accuracy performances. In particular, time difference-of-arrival (TDOA) is one of the widely used localization models. However, as TDOA measurement errors increase, the accuracy of the localization decreases. The accuracy of the TDOA measurement is influenced the accuracy of the localization and affected by multiple factors such as time synchronization, errors in sensor positions, missing data is caused by network attack. To reduce the influence of a sensor measurement error in localization, this paper proposes an improved localization algorithm for source localization using deep learning to address a TDOA measurements error or missing data in an asynchronous localization called DeepTAL. Unlike the conventional algorithm, DeepTAL can obtain highly accurate localization data in the presence of TDOA measurement errors or missing data. The algorithm starts with TDOA measurements without time synchronization. A network based on Long Short-Term Memory (LSTM) is then applied to achieve a stronger learning and better representation of the determined target state and TDOA prediction. The network can express features more abstractly at higher levels and increase recognition accuracy. After that, the target node is accurately located by TDOAs. We implement the DeepTAL algorithm on an asynchronous localization system with UWB signals. The experiments show that the proposed DeepTAL algorithm is efficient in improving the localization precision as measurement errors or missing data.

INDEX TERMS Localization, security, measurement error, missing data, deep learning.

I. INTRODUCTION

With the improvement of wireless technology, localization has emerged as an attractive solution, mainly in industrial settings for communication, sensing, and control of robotics using wireless networks [1]. Such applications require precise location information as otherwise the sensed data might be meaningless. There are three important metrics associated with localization: energy efficiency, accuracy, and security. Though the first two metrics have been researched extensively, the security metric has drawn the attention of researchers only recently. An important localization system is GPS due to its global coverage and ease of use. However, GPS often suffers from signal and multipath interference, especially in indoor environments. To further enhance the reliability and availability of a positioning system, ultra-wideband (UWB) has emerged as a promising technique to address this issue [2]. The nanosecond timestamp and high transfer data rate used by UWB localization systems enable them to make accurate signal measurements, which allows centimet-level positioning even in the presence of severe multipath interference. Moreover, since UWB signals have a very large bandwidth, UWB systems utilize low transmit power to avoid interference problems with other devices operating in the

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same frequency spectrum [3]. This paper focuses on an indoor localization system based on UWB.

Indoor localization systems can be divided into two categories: range-based and range-free. Range-based localization methods are widely investigated in the literature [4]. Among the available range-based localization systems, a popular positioning approach is the time-difference-of-arrival (TDOA) approach, which uses the time difference of reception of signals received by the various sensors and the network reference sensor. Generally, the crucial parameters used to solve the signal localization problem are information regarding times. Accuracy of the TDOA measurement is the main evaluation metric for estimated positions. However, the TDOA measurement error from measuring time signal reception sensors of the sensor network result in significant estimation error. The TDOA measure is affected by multiple factors such as the accuracy of synchronization, errors in sensor positions, missing data induced by communication failure or network attack and so on [5], [6]. Since these data can be easily tampered with, it is critical to ensure the integrity of these data.

For improve the TDOA localization accuracy, an effective method is to employ multiple anchors. All of the methods assume that the sensor positions are accurately known. However, in most practical scenarios, the sensor positions cannot be known or measured precisely. Examples include, the network is not carefully deployed or anchor selection is impractical. Sometimes, there could be malicious anchor nodes that give false location information to target nodes compelling them to compute incorrect location. The results presented in [8] show that even a small sensor position error could drastically and significantly degrade the localization accuracy. To get more available TDOA, the anchors need to be accurately placed. Many research studies have been devoted to localization in the presence of sensor location errors [9]–[12]. However, the superiority of these proposed algorithms come at the cost of increased computational complexity and some basic conditions have to be satisfied. Reference [13] focuses on the problem of locating multiple disjoint sources using TDOAs and frequency differences of arrival (FDOAs) in the presence of sensor position and velocity errors. The error of sensor positions affects the measurement accuracy, especially on a large scale. Unfortunately, regardless of the localization algorithms used, the TDOA measurement accuracy can be very sensitive to accurate knowledge of the sensor positions. Improvement of the accuracy of TDOA measurement sensor positions errors remains an important subject.

Unfortunately, TDOA measurement error is only one of the problems that adversely affect solutions based on TDOAs. The accuracy of localization is also limited by the dataset of TDOA values. As most of the proposed localization schemes were designed without taking security into consideration, and it is vulnerable to many security threats such as replay attacks, Sybil attacks, and wormhole attacks. Attackers can exploit these security loopholes to interfere with the localization process, or make the dataset incomplete. A security and reliability network is important for the transmission, especially in the moving state [31], [32]. Due to network attack, limited communication range, and environmental affects, which result in incomplete data or missing data that affect the accuracy of localization. In [16], given a large size dataset with few missing data values, one could simply remove all the records that include missing values. However, if the number of missing values is large, doing so causes a significant loss of information. Some simple methods replace the missing values with ''0''s or the mean of other values; however, this may introduce undesirable bias to the entire dataset [17] or even change the pattern of the data, especially data with a high variance [18]. Reference [19] exploits algebraic properties of a TDOA matrix to handle missing data along with additive noise and outliers. However, all the results in this study are based on the assumption of additive Gaussian noise, which is unrealistic in many practical applications. The incomplete TDOA values have to be processed and approximated before further data processing to be more reliable.

To overcome multiple factors required for, the implementation of the localization, many different algorithms try to acquire a localization with high precision from the range estimates. However, lots of obstacles such as multipath fading, shadowing effect, or scattering characteristics cannot be overcome due to the limitation of hard devices and environmental barriers, and thus, they affect the measurement characteristics. Since these external factors are very hard to model, it is hard to accurately measured via the conventional TDOA method. Over the last few years, deep learning (DL) techniques have shown great promise in many computer vision related tasks, e.g., object detection, object recognition, classification problems, etc. [20], [21]. Many studies focus on using the DL concept for localization, especially in and RSSI-based indoor localization. For instance, [22] proposed a feed-forward three-layered structure using a neural network for position localization in an indoor environment. The study results show that the proposed artificial neural network has the lowest error and the highest efficiency. Though there are many localization works that focus on fingerprinting-based localization, seldom has TDOA data been utilized by DL to extract features. DL learns high level features and a distributed data structure, which can represent original data better than a shallow feature. DL techniques can be used to train and obtain the core features for better localization performance. Therefore, we try to solve the TDOA measurement errors or missing data problem for localization using DL techniques.

In this paper, we propose DeepTAL, an algorithm for TDOA localization with sensor measurement errors or missing data, which achieves the localization using a deep learning approach. We measure the time difference with the ASync-TDOA model [7], which can measure the time difference between the target node and anchor nodes directly based on the timestamps. Our goal is to develop a TDOA localization algorithm that can handle TDOA measurement errors or missing data. To correct outliers or to predict missing data, we incorporate a deep long-short term memory (LSTM) network to train the data, which is a popular recurrent neural network (RNN) to handle time series data [23], [24]. The DeepTAL algorithm includes a data preprocessing module for collecting TDOA data. We collect the TDOAs and the difference of TDOAs suing ASync-TDOA model and then use zero mean normalization to normalize the features. After that, through an offline training phase that includes feature extraction, the DeepTAL network learns, and an object function. The DeepTAL network is based on LSTM to achieve a stronger learning and representation ability for training the determined target state and TDOA prediction. For the online phase, the training model is leveraged to predict the TDOA of the target between the target node and anchor nodes using the newly received TDOA measurement data from the ASync-TDOA model. Finally, the target node can be accurately located using the quantum-behaved particle swarm optimization (OPSO) algorithm for time difference. DeepTAL can predict missing data or correct outliers for localization and thus, improve the accuracy of localization. Furthermore, DeepTAL can accelerate location with lower data storage requirement in practical engineering.

The rest of this paper is organized as follows. In Section II, we review the studies in TDOA localization related to our work. Section III describes the TDOA measurement of ASync-TDOA. The details of DeepTAL and the performance of our prototype system are provided in Section IV and Section VI, respectively. Finally, conclusions are drawn in Section V.

II. RELATED WORK

A. LOCALIZATION SYSTEM

In the context of Industry 4.0, localizing people and objects in a precise and accurate way is a key requirement for future location-aware Internet of Things (IoT) applications [6]. The development of services based on localization has encouraged the effort of researchers in localization systems to maximize the accuracy, efficiency, and responsiveness of position estimation.

There are several different technologies such as WiFi, Bluetooth, ZigBee or UWB with different levels of accuracy, range and complexity used for an indoor localization system. UWB ranging is a promising approach that aims to achieve centimeter accuracy for indoor localization. Various localization systems have been proposed using UWB radios and very motivating results have been presented. Reference [2] analyzed the range accuracy, the ranging precision, and the positioning performance in a semi-industrial scenario that can be obtained with a Bayesian position estimation solution of three commercially available UWB positioning systems, Ubisense, DecaWave, and BeSpoon systems, under the same experimental conditions. However, cost is one of the leading constraints of Ubisense.

During the process of ranging, an estimation of the distance between any two nodes with TDOA is made. The range-based localization assumes that the distances between nodes are accurately and sufficiently measured. Generally, the real-time TDOA measurement between any two sensors occurs in the presence of biased measurement errors that affect the localization. Some studies focus on the localization in the presence of TDOA measurement errors. Reference [25] propose a general analytical framework, based on a Least Square (LS) method, to derive a novel statistical model for the range estimation error between a pair of UWB nodes. The proposed statistical model is then applied to improve the performance of a few illustrative localization algorithms in various realistic scenarios. An ECTSRLS technique was developed to suppress the residual NLOS range errors in [26]. Both static and mobile localization experiments were conducted to verify the new algorithm.

B. DEEP LEARNING IN A LOCALIZATION SYSTEM

With the development of artificial intelligence, deep learning approaches are have quickly emerged. Deep learning is utilized to train all the weights of a deep network for estimating the localization. Indoor localization has been gradually shifting to computational deep learning approaches, especially in the presence of range measurement errors or missing data.

Most of the existing deep learning-based localization methods are vision, fingerprinting, etc. Reference [27] proposes a novel framework for the fusion of depth data produced by a Time-of-Flight (ToF) camera and a stereo vision system with deep learning for extracting confidence maps to increase the accuracy of the vision-based depth estimation. [28] propose VLocNet, a new convolutional neural network architecture for 6-DoF global pose regression and odometry estimation from consecutive monocular images. [29] present a novel deep-learning-based indoor fingerprinting system using channel state information (CSI), which contains both an off-line phase for training and an on-line phase for localization. Reference [30] propose a novel indoor localization approach based on fingerprints of Received Signal Strength Indicator (RSSI) measurements. The approach utilized machine learning techniques using LSTM Neural Networks for location estimation.

Combined with the different collected data, many literatures based on deep learning have studied indoor positioning. [31] used an RNN to fuse the output of a standard marker-based visual pose system and IMU, thereby eliminating the need for statistical filtering. Reference [32] presented visual-inertial odometry by using a deep-learning network to fuse video and IMU data. Reference [33] present a deep learning-based approach to localizing a mobile robot using a 2D laser and an Inertial Measurement Unit. Reference [34] proposed a relative localization method of RFID tags via phase and RSSI based on Deep Learning (PRDL) to improve the accuracy of relative localization in one dimension, which is equivalent to the X latitude in STPP and HMRL.

However, a few studies have proposed to extract features for TDOA-based localization. Reference [35] propose an indoor TDOA-based three dimensional (3D) positioning

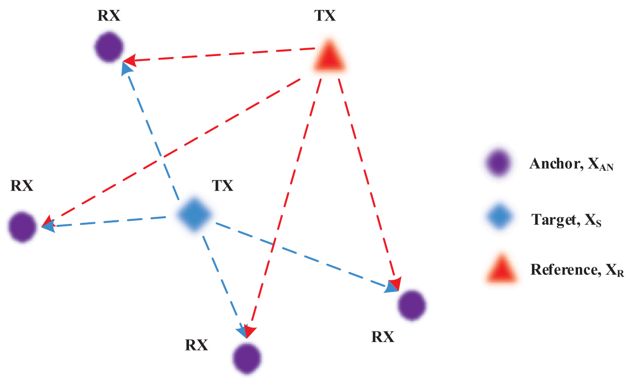


FIGURE 1. The communication of ASync-TDOA model.

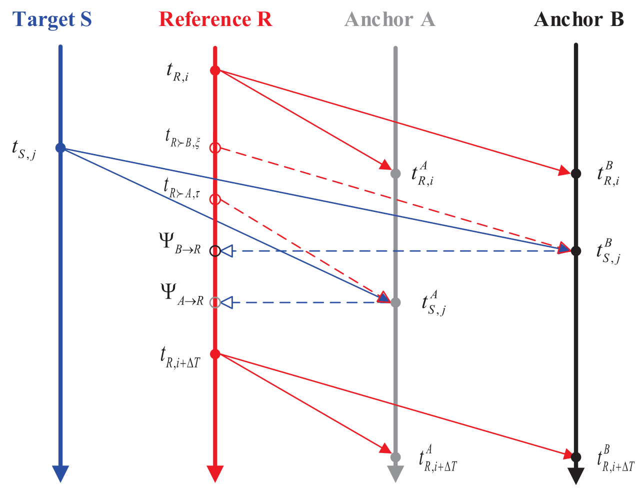


FIGURE 2. TDOA measurement without synchronization.

method with NLOS identification by SVM. Additionally, [36] propose a concept for intelligent radar systems employing UWB augmented by machine learning approaches to not only localize but also understand the location of a person or target within a building. In this paper, we combined with the recent advances in LSTM to generate novel solutions for TDOA measurement errors or missing data.

III. TDOA MEASUREMENT

In the proposed DeepTAL, we choose UWB signal with nanosecond accuracy for sample-based timestamps, and introduced ASync-TDOA model to measure the TDOAs [7]. The conventional TDOA measurement is as follows.

We consider the target node could send localization signals at any time and its position is donated by $\mathbf{X}_S$. The anchor nodes receive signals from the target node and the reference node, these positions can be denoted by $\mathbf{X_{AN}}$. During the measurement process, all anchor nodes record the timestamp and take turns to pass parameters to a central server to execute the computation tasks.

Ignoring the measurement noise, the distance between the target node and the i-th anchor node with time synchronization can be computed by

$$d_{AN_i} = cT_{AN_i} = \|\boldsymbol{X_S} - \boldsymbol{X_{AN_i}}\|, \quad \text{for} i = 1, \ldots, M \tag{1}$$

where c is the signal transmission speed, T_{AN_i} is the transmission time between the target node and i-th anchor node, $\|\cdot\|$ denotes the L2 norm, and X_{AN_i} is the localization of the i-th anchor node. The time difference between AN_i and AN_j can be given as

$$T_{AN_{i,j}} = T_{AN_i} - T_{AN_j} \tag{2}$$

The above calculations are based on the completion of time synchronization. In ASync-TDOA model, we measure the time difference in a one-way-based ranging by introducing the reference node $\mathbf{X_R}$ without time synchronization. The simple scenario to illustrate the ASync-TDOA model as shown in Figure 1. The reference node sends the signal periodically. The process of ASync-TDOA is as follows: For an anchor node, it needs to record timestamps that come from target node and the reference node, and then send them to the server. According to the record, the server can locally detect the interval of the arrival time of these two signals. By using reference node, the server can measure the time difference between the target node and anchor nodes directly based on the mapping values, still without any time synchronization. Figure 2 shows a typical TDOA measurement of ASync-TDOA.

Here, we describe how to accurately measure TDOA values by the ASync-TDOA model. The symbols used in our approach are defined in the notation list:

- $t_{S,j}$: The time of target node S sends the localization signal.
- $t^A_{S,j}$, $t^B_{S,j}$: The time of anchor nodes A and B received the localization signal, respectively.
- $t_{R,i}$, $t_{R,i+\Delta T}$, The time of the reference node R sends reference signals, respectively.
- $t^A_{R,i}$, $t^B_{R,i}$: The time of reference signals $t_{R,i}$ arrives at anchor node A and anchor node B, respectively.
- $t^A_{R,i+\Delta T}$, $t^B_{R,i+\Delta T}$: The time of reference signals $t_{R,i+\Delta T}$ arrives at anchor node A and anchor node B, respectively.
- $\Psi_{A\to R}$, $\Psi_{B\to R}$: The mapping values of $t^A_{S,j}$ and $t^B_{S,j}$, respectively.
- $t_{R\succ A,\alpha}$, $t_{R\succ B,\beta}$: The time of reference node R sends signal to anchor node A and B, and anchor node receive these signals at $t^A_{S,j}$ and $t^B_{S,j}$, respectively.

For all nodes, the TDOA is measured by the nodes' CPU timestamps, and there is no exact same timestamp in a short time. Hence, $t^A_{S,j}$ in the range of $t^A_{R,i}$ and $t^A_{R,i+\Delta T}$, $t^B_{S,j}$ in the range of $t^B_{R,i}$ and $t^B_{R,i+\Delta T}$. Then, according to the paper [7], the TDOA between $A$and B using mapping values is modeled by

$$T_{AB} = (t^A_{S,j} - t^B_{S,j})_{sync} \xRightarrow{\text{Mapping}} \Psi_{A\to R} - \Psi_{B\to R} \tag{3}$$

$$\Psi_{A\to R} - \Psi_{B\to R} = t_{R\succ A,\alpha} - t_{R\succ B,\beta} + \frac{d^{A,B}_R}{c} \tag{4}$$

With multiple TDOAs as well as locations of anchors or other data, we can set a TDOA-database $\mathcal{T}^{TDOA}$.

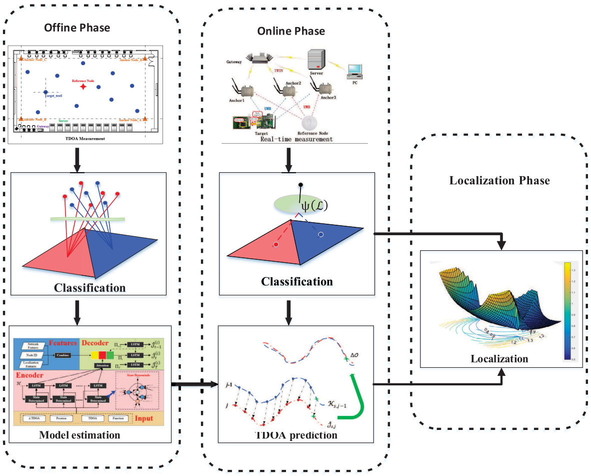


FIGURE 3. Architecture of DeepTAL network localization.

IV. SYSTEM DESCRIPTION

The problem of TDOA-based localization is formulated as an optimization problem, which is not easy to resolve because the measurement errors or missing data results in the optimization objective are nonconvex. We present a localization model, namely DeepTAL, to estimate the localization in the presence of TDOA measurement errors or missing data. In this section, we provide a brief overview of the system and then discuss the different components in detail.

A. SYSTEM OVERVIEW

The network architecture is deep in both vertical and horizontal directions, i.e., it has both top-down and lateral connections, as shown in Figure 3.

The DeepTAL localization is generally divided into three phases: offline phase (training phase), online phase (predicting phase) and localization phase. In the offline phase, we obtained a large number of data at each predefined target node for different locations, which can effectively describe the characteristics of the TDOAs for each location, and we stored them to a TDOA-database. A set of TDOAs readings is collected while in the offline phase, and which is only a small number of TDOA readings in a practical scenario. During the offline phase, we train a DeepTAL network model to predict TDOAs include the determined target state and predicted state. In the online phase, we should determine the target state first and then predict the TDOAs with measurement errors or missing data for each unknown location of the target. In the positioning stage, the measurement TDOA and the predicted TDOA are used to locate the target using OPSO algorithm, which can use the historical data such as the TDOAs or localizations of previous moments.

B. DATA PREPROCESSING

The data are one of the most important parts in any machine learning system, especially when dealing with deep networks. For that reason, gathering adequate data into a dataset is critical for any system based on deep learning techniques. Due to the sequence size requirement of the DeepTAL network, we first perform data preprocessing of the collected data and record TDOAs readings based on the UWB sensors. Specifically, we obtain 41550 rows of TDOAs in the laboratory scenario. The size of the data is approximately 31223 rows for training TDOAs and 10327 rows for testing. The original TDOA collected has a large range. To eliminate the dimensional influence among data features, this part uses zero mean normalization to normalize the features.

C. OFFLINE PHASE

The purpose of the offline phase is to construct the prediction model that will be exploited for the successive estimation of TDOA during the localization phase. The offline training module includes feature extraction, the deep LSTM network, and the loss function.

1) FEATURE EXTRACTION

Feature extraction can be formulated as a nonlinear mapping problem. We consider a network formed by $\mathbf{N_T}$ targets and $\mathbf{N_{AN}}$ anchor nodes. The position of $\ell(x_t, y_t)$ the target is in the set of $\mathcal{L}^T$. Because the anchor locations are known, the time between anchor nodes and samples are known. Ignoring the measurement noise, the TDOA between the **s**-th target node and the $\boldsymbol{i}$-th anchor node can be computed by $\mathcal{T}_s^i$. The measurement TDOA between **s**-th target node to $\boldsymbol{i}$-th anchor node and $\boldsymbol{j}$-th anchor node can be given as $\mathcal{T}_s^{i,j}$. We can define the measurement of TDOA set $\mathcal{T}^{TDOA}$ of **s**-th target node at time $\boldsymbol{t}$ as:

$$\mathcal{J}(s \in N_T, t) = \begin{bmatrix} \mathcal{T}_s^{1,1}, \mathcal{T}_s^{1,2}, \cdots \mathcal{T}_s^{1,N_{AN}} \\ \cdots \\ \mathcal{T}_s^{N_{AN},1}, \mathcal{T}_s^{N_{AN},2}, \ldots, \mathcal{T}_s^{N_{AN},N_{AN}} \end{bmatrix} \in \mathcal{T}^{TDOA} \tag{5}$$

We define $\gamma_{\mathbf{s},\Delta\mathbf{t}}^{\mathbf{i,j}}$ as the difference of the measurement TDOA between time $\mathbf{t}$ and time $\mathbf{t}-1$, which is $\gamma_{\mathbf{s},\Delta\mathbf{t}}^{\mathbf{i,j}} = \gamma_{\mathbf{s,t}}^{\mathbf{i,j}} - \gamma_{\mathbf{s,t-1}}^{\mathbf{i,j}}$. The difference of the TDOAs set $\mathbb{D}^{\eth}$ is:

$$\Delta\mathcal{J}(s, t \,\|\, t-1) = \begin{bmatrix} \gamma_{s,\Delta t}^{1,1}, \gamma_{s,\Delta t}^{1,2}, \cdots \gamma_{s,\Delta t}^{1,N_{AN}} \\ \cdots \\ \gamma_{s,\Delta t}^{N_{AN},1}, \gamma_{s,\Delta t}^{N_{AN},2}, \ldots, \gamma_{s,\Delta t}^{N_{AN},N_{AN}} \end{bmatrix} \in \mathcal{T}^{\Delta TDOA} \tag{6}$$

For better feature extraction, we defined the theory TDOA $\mathcal{K}(s \in N_T, t)$ in the set of $\mathbb{T}^{TDOA}$, and the difference of theory TDOAs in $\varepsilon(s, t\|t-1)$ the set of $\mathbb{T}^{\Delta TDOA}$. By using the TDOA and the difference of the TDOA as data for predicting TDOA, the dimension of the input data increase, which make it suitable for the proposed DeepTAL network, to strengthen the uniqueness of location features. Therefore, the TDOA can be predicted using the DeepTAL model in the presence of TDOA measurement errors. To predict TDOA diversity of the data with the TDOA and the difference of the TDOA, we define the confusion matrix for $\mathbf{N_T}$ different locations as:

$$\mathcal{H} = [\mathcal{J}, \mathcal{K}, \Delta\mathcal{J}, \varepsilon, \ell] \tag{7}$$

The data set is divided into two partitions: the training set that is used for learning and to fit the free parameters and the test set that is used to validate the model error and estimate the performance of the model. The training data is used during the learning process to solve the objective function related to the input and output. During the DeepTAL training phase, the TDOA and the difference of the TDOA are the training input and the prediction TDOAs are the training output.

2) DeepTAL NETWORK

The DeepTAL network consists of classification state and predicting state using LSTM networks. First, we use the distance difference set $\mathcal{T}^{\Delta TDOA}$ and $\mathbb{T}^{\Delta TDOA}$ for the determined target state. Then, DeepTAL makes different predictions for TDOA according to the movement or static state of the targets based on the confusion dataset $\mathcal{H}$.

LSTM is a class of networks where the output results depend not only on the current input value but also on the historical data [31]. Three gates have been largely used in the LSTM, and they automatically decide when to store or discard data and memory during training. Assume the DeepTAL network's input is $\mathbf{x_t}$ at time $\mathbf{t}$ and its hidden state is $\mathbf{h_{t-1}}$ and the memory cell is $\mathbf{c_{t-1}}$ of the previous LSTM unit. The forward propagation algorithm updates at time step k according to:

- Update the forgetting gate:

$$f(t) = \sigma\left[U_f x(t) + W_f h(t-1) + b_f\right] \tag{8}$$

- Update the input gate:

$$i(t) = \sigma\left[U_i x(t) + W_i h(t-1) + b_i\right] \tag{9}$$

$$a(t) = \tanh\left[U_a x(t) + W_a h(t-1) + b_a\right] \tag{10}$$

- Update the cell status:

$$C(t) = f(t) \odot C(t-1) + i(t) \odot a(t) \tag{11}$$

- Update the output gate:

$$o(t) = \sigma\left[U_o x(t) + W_o h(t-1) + b_o\right] \tag{12}$$

$$h(t) = o(t) \odot \tanh\left[C(t)\right] \tag{13}$$

where $\odot$ is the element-wise product of two vectors, σ is the sigmoid nonlinearity, tanh is the hyperbolic tangent nonlinearity, U is the corresponding weight matrices, b is the bias vectors, $i(t)$, $a(t)$, $f(t)$, $C(t)$ and $o(t)$ are the input gate, forget gate, input modulation gate, memory cell and output gate at time $\mathbf{t}$, respectively.

The back propagation through time (BPTT) algorithm, which is a gradient-based technique for training certain types of RNNs, is used for training the deep LSTM network. Therefore, we can use LSTM to control whether to forget the current cell value in the forget gate, if it should read its input in the input gate and whether to output the new cell value in the output gate in the process of determining the target state and TDOA prediction by learning suitable hyperparameters. Figure 4 represents the construction of DeepTAL networks.

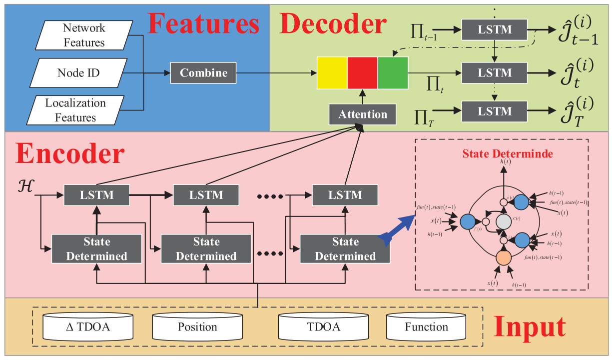


FIGURE 4. Construction of DeepTAL networks.

Note that we develop state determined mechanisms as depicted in the encoder, which capture target state correlations at each time by referring to the previous hidden state of the encoder and previous values of the sensors. In the decoder, we use a temporal attention to adaptively select the relevant previous time intervals for making predictions.

The construction of determining the target state network is as follows:

- The global training input has the following expression: $\mathcal{T}^{\Delta TDOA} = [\Delta\mathcal{J}(1), \Delta\mathcal{J}(2)\cdots, \Delta\mathcal{J}(s), \cdots \Delta\mathcal{J}(N_T)]$, the set of $\mathbb{T}^{\Delta TDOA}$ and $\mathcal{L}^T$.
- Input layer: It consists of three neurons, which respectively represent difference of measurement TDOAs, difference of theory TDOAs, last positions of targets.
- The hidden layer: LSTM structural unit with 30 LSTM units.
- Output layer: Two neurons, representing the state of target $\psi(\mathcal{L})$.
- Object function: cross entropy.

The construction of prediction the TDOA network is as follows:

- The training input has the following expression: $[\mathcal{J}(i), \mathcal{K}(i), \ell(i), \psi(\mathcal{L})]^T$, where $\mathcal{J}(i) \in \mathcal{T}^{TDOA}$, $\mathcal{K}(i) \in \mathbb{T}^{TDOA}$, $\ell(i) \in \mathcal{L}^T$, $\psi(\mathcal{L})$ is the state of the target.
- Input layer: It consists of four neurons, which respectively represent the measurement of TDOA, the theory TDOA, positions of targets and the state of the target.
- The hidden layer: LSTM structural unit with 40 LSTM units.
- Output layer: One neuron that represent the prediction TDOA set $\hat{\mathcal{J}}^{(i)}$.
- Object function: $\mathcal{F}_c$.

Therefore, the TDOA can be predicted by means of the DeepTAL model in the presence of TDOA measurement errors. The DeepTAL can express features more abstractly at higher levels, increases recognition accuracy, and achieve a stronger learning and better representation.

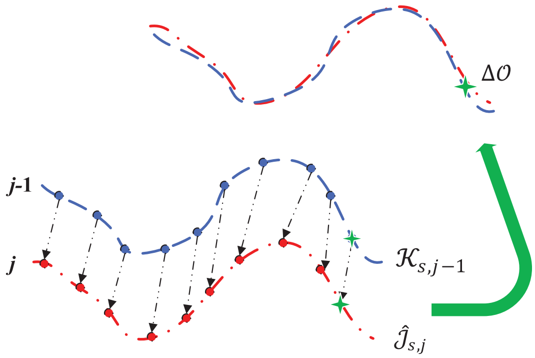


FIGURE 5. The difference of the TDOA error.

3) OBJECT FUNCTION

The object function quantifies the amount by which the prediction deviates from the desired values. Therefore, the lost function should be designed to train the DeepTAL so that its predicted poses are close to the ground truth. The object function contains two parts: a TDOA error and the difference of the TDOA error.

- TDOA error
  TDOA error is formulated as the Mean Square Error (MSE) of all TDOA measurements. The function aims to minimize the Euclidean distance between the ground truth and the estimated ones from the network, as well as the L2 regularization hyperparameter to avoid overfitting. We set samples with inputs and expected outputs $(\mathcal{J}, \mathcal{Y})$ and an object function $\mathcal{O}(\hat{\mathcal{Y}}, \mathcal{Y})$, where $\hat{\mathcal{Y}}$ represent the vector of prediction by given $\mathcal{J}$. The object function is as follows:
$$\mathcal{O}(\hat{\mathcal{Y}}, \mathcal{Y}) = \frac{1}{n}\sum_{0}^{n}\left\|\hat{\mathcal{J}}^{(i)} - \mathcal{K}^{(i)}\right\|_2^2 \tag{14}$$
  where $\hat{\mathcal{J}}^{(i)}$ is the prediction corresponding to the **i**-th training set element, $\mathcal{K}^{(i)}$ is the desired output for this sample, **n** is the train set length, $\| \|_2^2$ is the 2-norm.
- The difference of the TDOA error
  The difference of the TDOA error considers the prediction errors of LSTM. As shown in Figure 5, $\hat{\mathcal{J}}_{s,j}$ is a predicted TDOA value at time **j**, and $\mathcal{K}_{s,j-1}$ is the theory TDOA value at time $\mathbf{j-1}$ in matrix $\mathcal{T}^{TDOA}$. The difference of the TDOA error is the sum of the difference of TDOA at time **j** and $\mathbf{j-1}$, and can be defined as
$$\Delta\mathcal{O} = \frac{1}{n}\sum_{s=1}^{N_T}\sum_{j=1}^{T}\left\|\hat{\mathcal{J}}_{s,j} - \mathcal{K}_{s,j-1}\right\|_2^2 \tag{15}$$
  where $\hat{\mathcal{J}}_{s,j} \in \hat{\mathcal{T}}^{TDOA}$, $\hat{\mathcal{T}}^{TDOA}$ is the set of predicted TDOAs, and **T** is the time of points in samples. The more accurate the TDOA prediction is, the smaller the difference of the TDOA would be.

In summary, the object function considering these two different states for training is:
$$\mathcal{F}_c = \alpha \cdot \mathcal{O} + \beta \cdot \Delta\mathcal{O} + \lambda\left\|\theta^{(i)}\right\|_2^2 \tag{16}$$
where α and β are the weights to balance the object functions, and they are determined by the target state. λ is a factor to balance the weight of positions and orientations, and $\theta^{(i)}$ is the **i**-th element of the set of free parameters. When the target node is in a movement condition, the object function is mainly a TDOA error. Specifically, when the node is in a static condition, the object function contains a TDOA error and the difference of the TDOA error.

In the offline phase, the server will perform the training model with the dataset $\mathcal{H} = [\mathcal{J}, \mathcal{K}, \Delta\mathcal{J}, \varepsilon, \ell]$. The result is stored for use in the online phase.

D. ONLINE PHASE

After offline training, we need to test it with positions that are different from those used in the training stage. In the online phase, we predicted the TDOA value in the presence of TDOA measurement errors or missing data.

We first collect the TDOA in real-time by the ASync-TDOA model and build TDOAs dataset (as shown in the data preprocessing section and feature extraction). All anchor nodes receive a signal from the target node. In previous work [25], it has been proven that localization efficiency and accuracy is highly dependent on the anchor selection. Therefore, during the testing process we only consider the selection of the optimal anchor nodes.

Then, we predict the missing TDOA of the target by feeding the TDOAs data to the trained DeepTAL network. This function can be defined as:
$$Q : \begin{pmatrix} \mathcal{T}^{\Delta TDOA}, \mathbb{T}^{\Delta TDOA}, \mathcal{L}^T \longrightarrow \Psi(\mathcal{L}) \\ \Pi = [\mathcal{J}(i), \Delta\mathcal{J}(i), \ell(i), \Psi(\mathcal{L})]^T \longrightarrow \hat{\mathcal{J}}^{(i)} \end{pmatrix} \tag{17}$$

Finally, the prediction TDOAs are sent to the server and will be used to estimate the localization of the target node by the localization algorithm.

E. CALCULATING THE LOCALIZATION

In addition to the high accuracy requirement, an indoor positioning system should also have a short estimation process time and low complexity for mobile devices. In this case, we try to transform the indoor localization problem into an optimization problem and then, this problem can be optimized using the localization algorithm which is based on fuzzy weights (FWLo). The FWLo algorithm used the improved MSpPSOC (a multi sub-population particle swarm optimizer based on clustering) algorithm to calculate the positions respectively. Then, FWLo use the fuzzy comprehensive evaluation to obtain the result by multiple positions. In summary, the algorithm generation framework is illustrated in Figure 6.

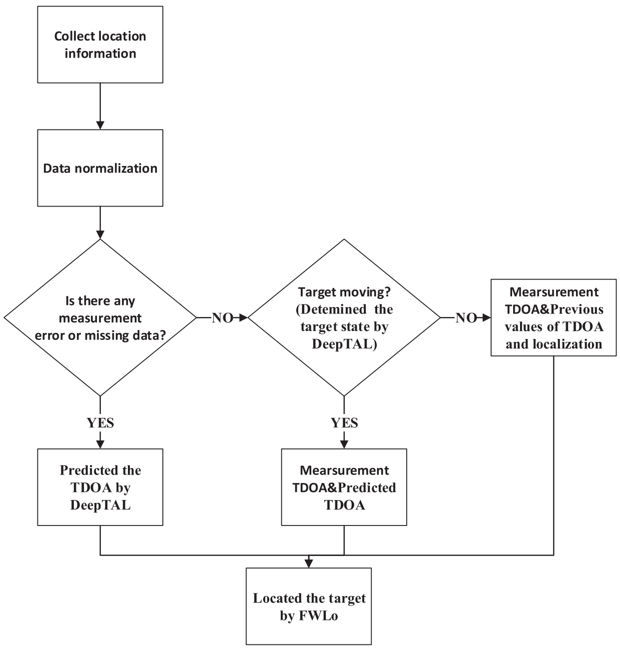


FIGURE 6. Framework of the localization algorithm.

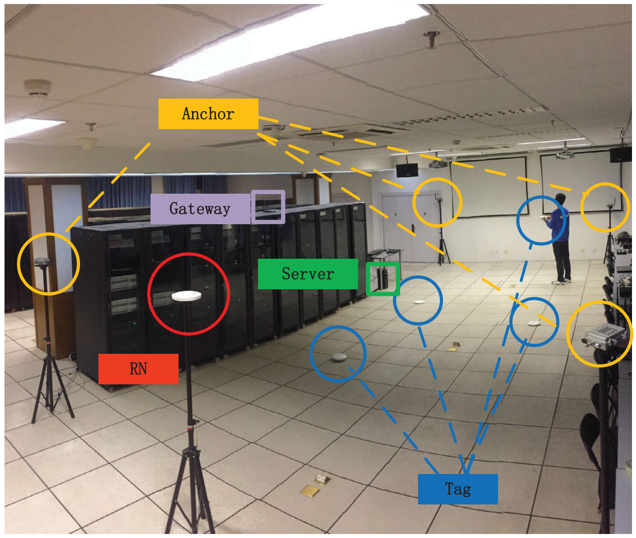


FIGURE 7. Experimental environment.

V. IMPLEMENTATION AND EXPERIMENTS

In this section, we describe our experimental testbed that uses deep learning for TDOA prediction. The experimental work consists of: A) experimental setup, B) data collection, C) prediction performance and D) localization estimation. These activities are described in detail next.

A. EXPERIMENTAL SCENARIO

We perform extensive experiments to examine the feasibility of DeepTAL working for localization in the presence of TDOA measurement errors or missing data. As shown in Figure 7, we test the performance of the proposed model in a 9.6*4.8 m^2 area in an indoor lab space to simulate the factory environment. For the sake of simplicity, we consider a 2D localization model to compare with other models. We predict the time difference and estimate the localization in this environment to evaluate the proposed model.

The implemented system consists of four anchor nodes and a reference node. The coordinates of the anchor nodes are $A = (9.6\text{ m}, 0)$, $B = (0, 0)$, $C = (0, 4.8\text{ m})$, $D = (9.6\text{ m}, 4.8\text{ m})$. The coordinate of the reference node is $R = (9.6\text{ m}, 2.4\text{ m})$. In all experiments, the target node is static and transmits a packet every 300 ms.

The working process of the test is as follows:

(a) Collect the TDOAs and the difference of the TDOAs using the ASync-TDOA model.

(b) Build the confusion matrix $\mathcal{H} = [\mathcal{J}, \mathcal{K}, \Delta\mathcal{J}, \varepsilon, \ell]$.

(c) Determine the objective function and input matrix to $[\Delta\mathcal{J}, \varepsilon]$ train the model of determine the target state network.

(d) According to the classification results, use the input matrix H to train the model for prediction of the TDOA.

(e) Input the TDOA matrix of real-time collection to judge whether the data are completed.

(f) Use the training model to obtain the predicted TDOA.

(g) Estimate the localization of the target node by FWLo.

B. DATA COLLECTION

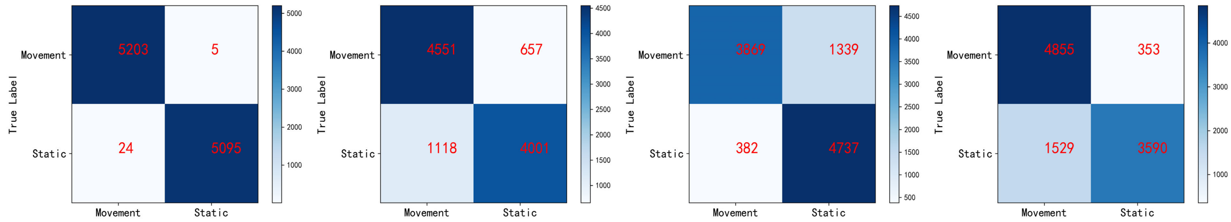
To obtain enough data for training, we use the DecaWave DW1000 as radio transceivers, which is compliant with the IEEE802.15.4 standard. The controlling framework of transmitting or receiving the timestamp was actualized by an STM32f105 chip with Contex-M3. We set 22 targets located one meters apart from each other to obtain 2000 samples for each target. In total, our data set contains 5000 samples with their respective physical coordinates. According to the test results of the Asyn-TDOA model, when the timestamp difference between the target to two anchor points is greater than 2000, it is useless data. At last, we use 31223 rows for training TDOAs and 10327 rows for testing.

C. PREDICTION PERFORMANCE

The goal of the experimental assessment is to study two different networks of the determined target state and TDOA prediction.

During the TDOA predicting, we should determine the target state first. We should basically analyze the performance of the classification for determining the target state. Figure 8 shows the confusion matrices of differences models and Figure 9 shows the AUC and the curve of receiver operating characteristics (ROC) in difference models for the target state classification. The AUC of our model is 0.9979 for the datasets. Comprehensively, our model obtains a slightly higher performance on the dataset.

To qualitatively demonstrate the effectiveness of the DeepTAL model, the tests for different models in the same dataset are illustrated in Table 1. More details about the classification of the 5 algorithms are reported respectively. As it can



(a) DeepTAL (b) KNN (c) SVM (d) Logerg

FIGURE 8. Confusion matrices of models.

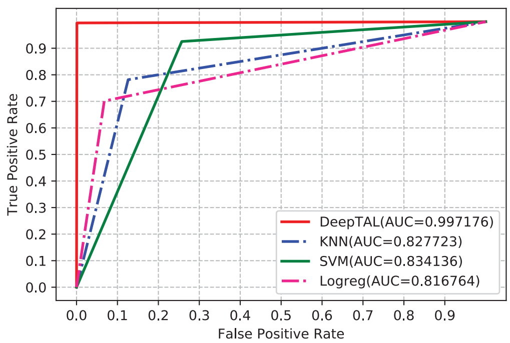


FIGURE 9. ROC for state classification.

TABLE 1. The performance of classification models with the training dataset.

Model	DeepTAL	KNN	SVM	Logerg
Accuracy	0.997289	0.832091	0.836254	0.811852
Precision	0.999417	0.863338	0.787248	0.9119
Recall	0.995163	0.789514	0.922035	0.690849
f1	0.997286	0.824778	0.849327	0.786131

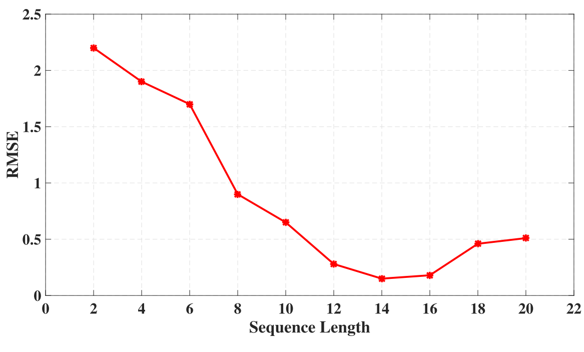


FIGURE 10. Sequence length of RMSE.

be observed, the DeepTAL model produces better results than the others do. Among these models, the DeepTAL model outperforms others for the average accuracy, which verifies the effectiveness of the proposed model.

To objectivity evaluate the performance of the DeepTAL, we analysis the RMSE of the difference sequence length. As shown in Figure 10, the RMSE reaches the optimal result (i.e. the minimum) when the sequence length is 14. The DeepTAL obtain the best prediction performance when the sequence length of the dataset is 14.

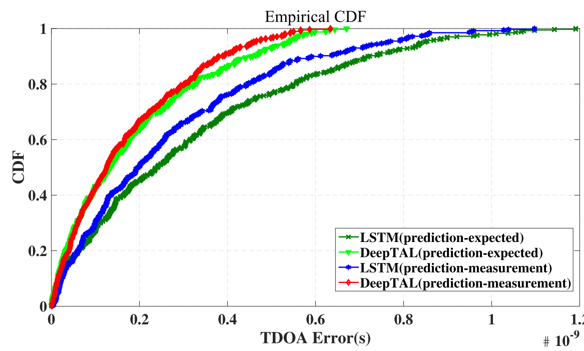


FIGURE 11. TDOA errors.

We use multiple criteria to evaluate the performance of the DeepTAL approach for TDOA prediction. We performed tests on DeepTAL and compared them with LSTM using RMSE. The proposed approach is compared to LSTM algorithms that exist in the literature. DeepTAL and LSTM are implemented using the same experimental scenario for a fair comparison. The average TDOA prediction TDOAs for DeepTAL and LSTM against different anchors are shown in Figure 11. As seen, DeepTAL clearly outperforms LSTM with the maximum error of $0.6*10^{-9}$ s compared with $1.2*10^{-9}$ s. 80% of the DeepTAL model errors are within $0.3*10^{-9}$ s, which is much lower than $0.5*10^{-9}$ s of the LSTM.

Moreover, we evaluated the expected value and estimated TDOAs for DeepTAL as shown in Figure 11. As seen in the results, DeepTAL is able to stay close to the expected value for TDOA measurement errors or missing data. The results also indicate that DeepTAL is capable of predicting TDOA data by state determination mechanism and interpreting the localization information from the current TDOA data and previous localization information saved by the internal hidden memory of the LSTM units. Thus, we can conclude that DeepTAL makes effective for the TDOA prediction.

D. LOCALIZATION ESTIMATION

In the following we show the performance of different localization algorithms. The network is fine-tuned with real data in practice.

Figure 12 plots the cumulative distribution function (CDF) of localization errors between the proposed DeepTAL and

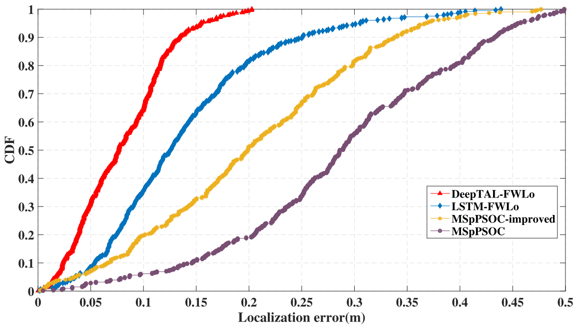


FIGURE 12. CDF of localization errors.

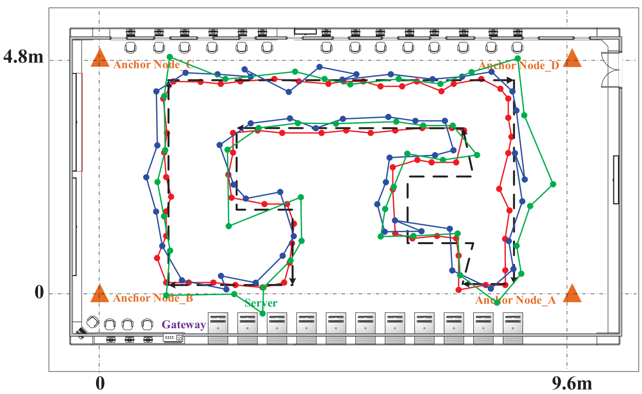


FIGURE 13. Trajectories of localization in difference algorithms.

other models in the lab experiment using the real-time data. The results of the DeepTAL-FWLo outperform the ones of the other algorithms. As shown in Figure 12, there are approximately 64.53% of the localization errors with the proposed DeepTAL-FWLo system are under 0.1 m, while 37.44% of the localization errors with the LSTM-FWLo algorithm are under 0.1 m. Moreover, DeepTAL-FWLo has 93.6% of the test locations with location errors less than or equal to 0.15 m, while it is 32.51% for the MSpPSOC-improved algorithm. DeepTAL-FWLo achieves a maximum error of 0.202 m, which is much better than the 0.499 m maximum error of the MSpPSOC. Apparently, the proposed DeepTAL-FWLo system is more accurate for the lab environment.

The trajectories of localization using the real-time data are given in Figure 13, where the black dashed line is the ground truth, the red line is the FWLo with DeepTAL predicted, the blue line is the FWLo with LSTM predicted and the green line is the MSpPSOC without TDOA predicted. As it can be observed, the DeepTAL-FWLo can achieve higher accuracy by predicting the TDOA with measurement errors, outliers or missing data. Since corners usually cause sudden geometry changes, MSpPSOC method may suffer from large errors at corners.

The experiments validate that the proposed DeepTAL network can accurately predict TDOA, which validates the design of the deep learning. The main reason for the accuracy is the state determined mechanisms have stronger location diversity, which carries more location features. Furthermore, the proposed DeepTAL network can effectively extract rich location features from the data to achieve enhanced localization performance. Therefore, the reliability of the prediction has been improved using the DeepTAL-based architecture.

VI. CONCLUSION

In this paper, we presented the DeepTAL model for the time difference prediction between the target node and anchor nodes in the presence of TDOA measurement errors or data missing and implemented it on a platform with UWB signals. In the TDOA range-based localization, the accuracy of TDOA measurement affected the precision of the localization, and the TDOA measurement is affected by multiple factors such as time synchronization, errors in sensor positions, data missing and so on. Compared with the existing literature, we investigated the feasibilities of DeepTAL by extensive experimentation for reducing the influence of the sensor measurement error for localization. The results showed that DeepTAL can prediction the time difference by introducing the state determination with LSTM model and provide available accurate prediction. During the process of the localization, DeepTAL can predict TDOA accurately in the presence of TDOA measurement errors or missing data, and obtain more localization information from the current TDOA data and previous localization information to estimate the localization in real time to improve the localization precision.

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