# Poster: Basic Study of BLE Indoor Localization using LSTM-based Neural Network

Kenta Urano
Kei Hiroi
vrano@ucl.nuee.nagoya-u.ac.jp
k.hiroi@ucl.nuee.nagoya-u.ac.jp
Nagoya University
Aichi, Japan

Takuro Yonezawa
Nobuo Kawaguchi
yonezawa@nagoya-u.jp
kawaguti@nagoya-u.jp
Nagoya University
Aichi, Japan

## ABSTRACT

In this paper, LSTM-based neural network is applied to indoor localization using mobile BLE tag's signal strength collected by multiple scanners. Stability of signal strength is a critical factor of wireless indoor localization for higher accuracy. While traditional methods like trilateration and fingerprinting suffer from noise and packet loss, deep learning based methods perform well. We focus on large-scale exhibition where wireless signal gets unstable due to many people. Proposed neural network consists of fully connected layers for noise removal and LSTM layers for time-series feature extraction. The network takes the time-series of signal strength as input and outputs the estimated location. In the evaluation, the number of layers is changed to find the optimal structure. As a result, the best configuration achieved the error of 2.44m at 75 percentile for the data of a large-scale exhibition in Tokyo.

## CCS CONCEPTS

• **Information systems → Location based services**; • **Computing methodologies →** *Supervised learning by regression.*

## KEYWORDS

indoor localization; BLE; deep learning; LSTM

**ACM Reference Format:**

Kenta Urano, Kei Hiroi, Takuro Yonezawa, and Nobuo Kawaguchi. 2019. Poster: Basic Study of BLE Indoor Localization using LSTM-based Neural Network. In *The 17th Annual International Conference on Mobile Systems, Applications, and Services (MobiSys '19), June 17–21, 2019, Seoul, Republic of Korea.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3307334.3328624

## 1 INTRODUCTION

Participants' activities at an exhibition event such as moving path or duration of stay at a booth are useful for the organizer to decide booth arrangement and for exhibitors to select what to display. To collect this information, we need participants' location. Because GPS signal is weak indoors, many indoor localization methods are proposed. We focus on Bluetooth Low Energy (BLE) based localization. We use mobile BLE tag with fixed scanner so that we can locate participants by providing BLE tags at the exhibition entrance.


*MobiSys '19, June 17–21, 2019, Seoul, Republic of Korea*

ACM ISBN 978-1-4503-6661-8/19/06.
https://doi.org/10.1145/3307334.3328624

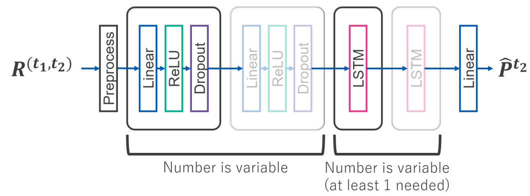



**Figure 1: Network structure.**

In this paper, we propose LSTM-based BLE localization to mitigate the effect of noise and packet loss. BLE signal gets unstable due to many people and mobile devices in a large-scale exhibition event. While existing methods like trilateration and fingerprinting suffer from signal instability, deep learning based methods are reported to achieve higher accuracy. In Wi-Fi based localization, WiDeep[1] uses stacked denoising autoencoder and estimates the location based on the similarity of query signal strength and denoised signal strength. Xiao et al.[2] proposed BLE localization which uses kNN and denoising autoencoder.

Proposed neural network takes time-series of signal strength and outputs estimated location because combining deep learning and an existing method needs complex parameter tuning for both methods. To decide the optimal structure, we evaluate estimation accuracy by changing the number of layers.

## 2 NEURAL NETWORK COMPOSITION

The neural network consists of FC units (fully connected, ReLU, dropout layers), and LSTM layers. FC units are expected to correct signal strength by removing noise or interpolating missing signal strength. Basic structure is shown in Fig.1. The number of FC units and LSTMs can be changed to find the optimal structure. Input $\boldsymbol{R}^{(t_1,t_2)}$ is the matrix of signal strength defined by (1), where $r_n^t$ is the signal strength captured by scanner $n$ at time $t$ and $N$ is the number of scanners. Output is the estimated location $\hat{\boldsymbol{P}}^{t_2} = (\hat{x}^{t_2}, \hat{y}^{t_2})$ at time $t_2$.

$$\boldsymbol{R}^{(t_1,t_2)} = \begin{vmatrix} r_1^{t_1} & r_2^{t_1} & \cdots & r_N^{t_1} \\ r_1^{t_1+1} & r_2^{t_1+1} & \cdots & r_N^{t_1+1} \\ \vdots & & \ddots & \\ r_1^{t_2} & r_2^{t_2} & \cdots & r_N^{t_2} \end{vmatrix} \tag{1}$$

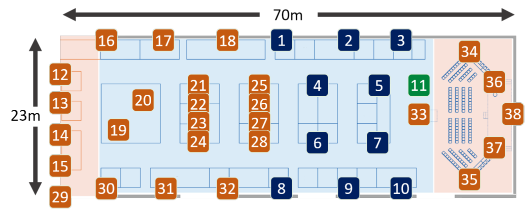



**Figure 2: Target area and scanners' location.**

Loss function is configured as (2). $\boldsymbol{P^{t-1}}$ and $\boldsymbol{P^t}$ are the ground truth locations. $PD$ and $\widehat{PD}$ are the distances of two locations defined as (3) and (4). $w_m$, $w_c$, and $w_r$ are the weights for each loss component. $f_1$, $f_2$, and $f_3$ are the funtions which calculates mean squared error, cosine similarity, and ReLU, respectively.

$$\begin{aligned} & L(\boldsymbol{\hat{P}^t}, \boldsymbol{P^{t-1}}, \boldsymbol{P^t}) \\ & \quad = w_m f_1(\boldsymbol{\hat{P}^t}, \boldsymbol{P^t}) \\ & \qquad + w_c(1 - f_2(\boldsymbol{P^t} - \boldsymbol{P^{t-1}}, \boldsymbol{\hat{P}^t} - \boldsymbol{P^{t-1}}))PD \\ & \qquad + w_r f_3(\widehat{PD} - PD) \end{aligned} \tag{2}$$

$$PD = Distance(\boldsymbol{P^t}, \boldsymbol{P^{t-1}}) \tag{3}$$

$$\widehat{PD} = Distance(\boldsymbol{\hat{P}^t}, \boldsymbol{P^{t-1}}) \tag{4}$$

First term is the distance between ground truth and estimated location. Second term is related to direction error weighted by distance between two locations of ground truth at $t-1$ and $t$. Third term only works when estimation goes too far from ground truth.

## 3 EVALUATION

To find optimal structure, estimation accuraries are evaluated for 10 patterns of network configurations. Target environment is G-EXPO 2016 exhibition held in Miraikan Museum in Tokyo. Target area and the locations of scanners are shown in Fig.2.

The amount of training data using GEXPO experiment is insufficient for better result, we use simulated data for training the network. Training uses 160,000 simulated data for 200 epochs and 78,000 GEXPO data (from 20 subjects) for additional 100 epochs. Testing uses GEXPO data not used in the training.

Estimation results based on error distance at cumulative probability of 0.5, 0.75, 0.9 are shown in Table1. 1 FC unit and 1 LSTM configuration marked the best at all cumulative probability. Expect that 0 FC unit or 4 FC units with 1 LSTM do not perform well, estimation accuracy does not change when using more layers. As a result, the configuration of 1 FC unit and 1 LSTM is better because of higher accuracy with simple structure.

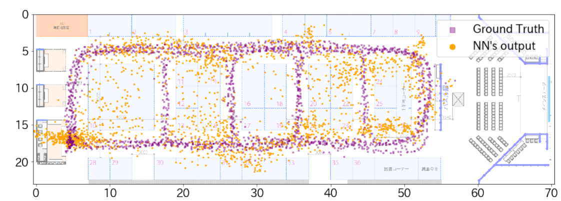
Qualitative result are shown in Fig.3. From Fig.3b which corresponds to the worst configuration, estimation on the left half of the area is unsuccessful. Fig.3a corresponds to the best condition, however, the convergence of the estimated points onto the ground truth is not enough.

## 4 CONCLUSIONS

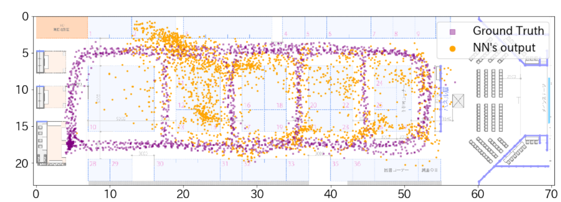
In this paper, we proposed LSTM-based BLE localization which takes signal strength as input and outputs estimated location. The neural network consists of fully connected layers for signal strength correction and LSTM layers for time-series feature extraction. To find out the optimal structure, estimation accuracies of 10 configurations are evaluated. As a result, 1 FC unit with 1 LSTM is the best configuration with 2.44m error at cumulative probability of 0.75. Because estimated points have large variance, further modification of the neural network is needed for better convergence of them onto the ground truth.

**Table 1: Error at cumulative probability of 0.5, 0.75, 0.9**

| FC units | LSTM | Error at cum. prob.[m] | | |
|---|---|---|---|---|
| | | p=0.5 | p=0.75 | p=0.9 |
| 0 | 1 | 2.19 | 3.83 | 6.15 |
| 1 | | 1.30 | 2.44 | 4.26 |
| 2 | | 1.80 | 2.88 | 4.94 |
| 3 | | 1.60 | 3.07 | 4.39 |
| 4 | | 2.36 | 4.59 | 10.1 |
| 0 | 2 | 1.87 | 3.37 | 5.70 |
| 1 | | 1.48 | 2.97 | 5.70 |
| 2 | | 1.66 | 2.93 | 4.62 |
| 3 | | 1.51 | 2.85 | 4.95 |
| 4 | | 1.56 | 3.02 | 4.83 |




**(a) Good: 1 FC unit, 1 LSTM.**




**(b) Bad: 4 FC units, 1 LSTM.**

**Figure 3: Qualitative results.**

## ACKNOWLEDGMENTS

This work was supported by JSPS KAKENHI Grant Number JP17H01762.

## REFERENCES

[1] Moustafa Abbas, Moustafa Elhamshary, Hamada Rizk, Marwan Torki, and Moustafa Youssef. 2019. WiDeep: WiFi-based Accurate and Robust Indoor Localization System using Deep Learning. In *PerCom 2019*. 232–241.

[2] Chao Xiao, Daiqin Yang, Zhenhong Chen, and Guang Tan. 2017. 3-D BLE Indoor Localization Based on Denoising Autoencoder. *IEEE Access* 5 (2017), 12751–12760.