Vol.2022-HCI-200 No.16
Vol.2022-UBI-76 No.16
2022/11/8

Preliminary Investigation of Distance Estimation between Smartphones via Wi-Fi Round Trip Time

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概要：Estimating the physical distance between mobile devices such as smartphones with their Wi-Fi modules in an indoor environment has many potential real-world applications such as enhancing indoor navigation, analyzing and discovering communities, Wi-Fi geo-fencing, etc. Such distance estimation tasks have been conducted using Received Signal Strength Indication (RSSI), which leverages the strengths of signals from nearby Wi-Fi Access Points (APs). However, the imprecision of RSSI measurements has limited the performance of the RSSI-based methods. Recently, IEEE 802.11mc introduced Wi-Fi Round Trip Time (RTT) protocol, which enables distance estimation between devices and nearby APs by calculating the time-of-flight of signals, and has greatly improved the accuracy of indoor ranging. Therefore, this study presents a novel method for distance estimation between devices using Wi-Fi RTT, leveraging a graph neural network (GNN) to fully capture the geometric information among smartphones and nearby APs.

Keywords: Ubiquitous Computing, Wi-Fi Round Trip Time, Graph Neural Network

1. Introduction

In recent years, Wi-Fi technology has become very popular with the proliferation of wireless smart devices such as smartphones and tablets; its infrastructure has been widely deployed in both public and private environments, including shopping malls, airports, offices, and private residences [1][2]. Nowadays, many mobile services rely on the user's position to deliver appropriate information, such as navigation, wireless payment, communication, etc. Although outdoor positioning technologies through Global Navigation Satellite Systems (GNSSs) have been well-developed, the non-line-of-sight (NLoS) to the satellites hinders the accuracy of indoor positioning [3]. The prevalence of Wi-Fi access has drawn attention from researchers on proximity detection of devices using Wi-Fi, which is to determine the locations of the Wi-Fi-enabled devices in indoor environments [4]. Such technologies have efficiently improved the accuracy of indoor positioning. On the other hand, distance estimation using Wi-Fi is attracting more attention, which is to estimate the physical distance between Wi-Fi-enabled devices. It has many real-world applications such as enhancing the accuracy of indoor navigation, analyzing and discovering communities, Wi-Fi geo-fencing, etc [2].

The most common approach to distance estimation using Wi-Fi has been based on Received Signal Strength Indication (RSSI), which is to leverage the strength of signals emitted from nearby Wi-Fi Access Points (APs). However, the imprecision of RSSI measurements has limited the performance of the RSSI-based methods [2]. In addition, the feed-forward neural network based on hand-crafted features, which is often used to analyze the collected information, cannot fully leverage the geometric information of APs and smartphones due to its comparatively straightforward structure.

In recent years, IEEE 802.11mc introduced Wi-Fi Round Trip Time (RTT) protocol, which enables distance estimation between devices and nearby APs by calculating the time-of-flight of signals, and has greatly improved the accuracy of indoor ranging [5]. Therefore, this study

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presents a novel method to estimate the physical distance between smartphones and APs using Wi-Fi RTT, while leveraging a graph neural network (GNN) to fully capture the geometric information among them. **Figrue 1** depicts the use case of our approach, i.e., when the distance between smartphones and nearby APs are known and the distance between smartphones is unknown. The main contribution of our research includes the following:

- To the best of our knowledge, this is the first study that estimates the physical distance between two smartphones using Wi-Fi RTT.
- To the best of our knowledge, this is the first study that leverages GCN on predicting physical distance between objects.

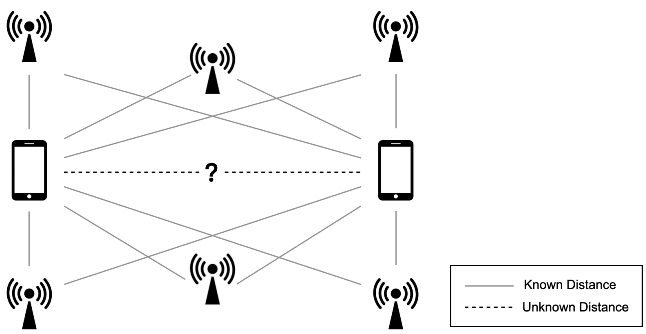

図 1 Relationship between Smartphones and APs

2. Related Works

2.1 Indoor Positioning with Wi-Fi RTT

Overview: Traditionally, indoor positioning and ranging techniques are divided into fingerprinting approaches and propagation approaches. Conventional fingerprinting approaches for indoor positioning with Wi-Fi typically consist of two phases the training phase, and the positioning phase [6]. In the training phase, the received Wi-Fi measurements are observed and collected at a number of known coordinates in order to construct a feature map of the surrounding environment. In the positioning phase, the position of the device can be estimated by correlating the measured information with the preconstructed map. The coordinates corresponding to the closest match are returned as the estimate for the receiver position.

In recent years, the focus of indoor positioning research has been gradually shifted to base on Wi-Fi RTT since the introduction of IEEE 802.11mc standard. This new protocol allows smart devices to estimate their distances to nearby Wi-Fi APs; hence, many studies have been conducted regarding the performance of indoor positioning using RTT, and how to increase its precision with different approaches.

Fingerprinting Methods: Hashem et. al. [7] presents an indoor location determination system that combines the advantages of the fingerprinting method and time-based ranging techniques. Their model overcomes challenges such as NLoS, multipath, signal interference and achieve a submeter accuracy in two different testing environments.

Despite its accuracy, fingerprinting methods are usually time-consuming and expensive because the users have to go through preliminary investigation of the target environment to collect site information and construct a feature map. It is also difficult to implement in a real-world scenario, where the site information, such as location of APs and structure of the indoor environment is usually not directly available [8]. On the other hand, propagation methods are usually more time-saving because they do not require preliminary investigation and feature map construction. As a result, their predictions are not as accurate as fingerprinting methods.

Propagation Methods: Different approaches have been leveraged to increase the accuracy of propagation methods. Cao et. al. [9] presents a propagation-based study that increases the localization accuracy by leveraging an indoor position method based on line-of-sight (LoS) identification and range calibration. They first designed a NLoS and LOS identification algorithm based on a scenario recognition model using Gaussian process recognition (GPR). Also, a range calibration model using nonlinear least-squares fitting is established to correct the measured LOS distance. When performing positioning, the environment is first identified by the scenario recognition model, and a LOS distance will be obtained based on it. The LOS distance will then be calibrated by the range calibration model before being used to estimate the smartphone's position using the least square algorithm. Their proposed model achieves a submeter accuracy, which is an improvement compared to some other positioning techniques such as using RSSI.

Han et. al.'s [10] research also dedicate to address the problem of RTT bias, which is caused by signal detour along with NLoS paths, by proposing a novel positioning algorithm that estimates the location of users by integrating RTT and pedestrian dead reckoning (PDR) measurements detected by the inertial measurement units of smartphone. PDR is able to provide the geographic relation among adjacent locations, and derives the sequence of the locations of the user in order to avoid deviation from the user' s mobility trajectory. Specially, when conducting Wi-Fi positioning, they first jointly estimate an RTT bias of each AP and the step length of the user by considering their geometric relation, then construct the user' s relative trajectory with respect to each AP. After that, the trajectory alignment process, which aligns the relative trajectory of every AP into a single one, is achieved before estimating the sequence of the absolute locations of the user from the aligned global coordinate system. This proposed method also yields a submeter accuracy in LoS environments but not as good in NLoS environments, but is still an improvement compared to conventional multilateration techniques.

2.2 Distance Estimation between Wireless Devices Using Wi-Fi RSSI

Binary Proximity Detection: Proximity detection is another popular field in studies using Wi-Fi devices, especially during the ongoing COVID-19 pandemic. Van Hyfte et. al. [4] mentions that some smartphone applications aim to alert their users when they come within close range to individuals infected with COVID-19, and report potential exposures to public health authorities so that they can prevent spread of the virus. Therefore, it is important to monitor proximity of users. They propose a new method of detecting proximity of two Wi-Fi-enable devices using Wi-Fi measurements, in contrast to conventional methods which mostly leverage Bluetooth Low Energy. The proposed method is a binary classifier that takes AP features and RSSI measurements from two MAC addresses as input, and predicts whether or not two fingerprints are in immediate physical proximity. Those within 2.25 meters of range are labeled "Close" to each other, and "Far" from each other otherwise. Their model results in an average accuracy of around 70%.

Accurate Distance Estimation: Although binary proximity detection is valuable to applications such as disease control, sometimes we need to predict a precise physical distance between two devices for other purposes. To solve this problem, Nakatani et. al. [2] proposes a new method using RSS data. A major contribution of their work is that they do not require labeled training data regarding the presence of obstacles between two smartphones, while taking the obstacles into account by applying a wall detection model that computes the probability of having walls between two locations. Then the distance estimation is performed using a neural network that leverages the presence of walls. Although this environment-independent distance estimation model no longer needs input of site information, the imprecision of RSSI measurements has limited its performance. The accuracy with a mean absolute error of bigger than 3 meters needs to be improved for real-world implementation purposes. In this study, we employ RTT measurements and a graph neural network to achieve precise distance estimation.

3. Proposed Method

3.1 Overview

As mentioned in Section 2, while the majority of current RTT-based indoor ranging methods are based on the fingerprinting method for its excellent accuracy, our method features a propagation method mainly due to its convenience and practicality in daily life. Compared to other propagation methods which usually leverage a simple feed-forward neural network, we propose a novel approach using GNN which is believed to be capable of better utilizing the geometric information. Furthermore, rather than focusing on improving the distance estimation accuracy between a smartphone and nearby APs, we aim to predict the physical distance between two smartphones, which can be more practical for real-world applications.

Therefore, we propose RTT-GCN, an algorithm based on graph convolution network (GCN) for distance estimation using RTT. With RTT-GCN, we aim to exploit the geometric information from Wi-Fi RTT data to learn meaningful representations for the unknown physical distance between two smartphones.

3.2 Graph Structure

In this paper, we are leveraging graph neural networks to handle the geometric information collected. An undirected graph G can be defined as $G = (V, E)$ that consists of a set of nodes $V = \{v_1, v_2, ..., v_n\}$ and a set of edges $E \subseteq V \times V$. It can also be represented by an adjacency matrix A, where $A_{i,j} = 1$ represents there is an edge between node i and node j, and $A_{i,j} = 0$ represents there is no edge between them.

As shown in the left half of **Figure 2**, we construct a graph consisting of nodes corresponding to devices (smartphones and APs) and edges corresponding to the distances among the devices. However, when we regard devices as nodes and the links among them as edges of a graph, the measurements, including RTT and RSSI data, will be seen as edge features. However, a limitation about current graph neural networks is that they are mostly focusing on the nodes and node features, while treating edges as a simple binary information.

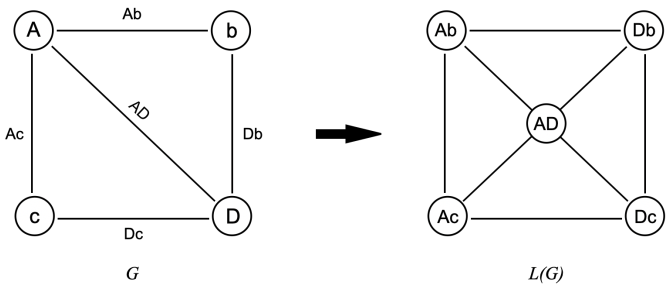

図 2 Transformation from original graph G to line graph L(G)

To solve this problem, we utilize the line graph technique as introduced in Cai et. al.'s [11] paper. In a line graph structure, the edges from the original graph G will be converted into nodes in the new line graph $L(G)$. Therefore, if G has m nodes and n edges, $L(G)$ will have n nodes. New edges will be formed based on whether the two new nodes of $L(G)$, or in other words, two edges of G, share a common node in G.

After the line graph transformation as shown in the right half of **Figure 2**, we will be able to treat information such as RTT and RSSI measurements as node features, thus analyzing this information using normal graph neural networks.

3.3 Network Structure and Network Training

Figrue 3 shows the network structure of RTT-GCN. The inputs of the model include standardized RTT measurements, an identifier of each measurement, and the adjacency matrices describing the relationship of devices in each measurement, i.e., graph structures. The x in the figure represents the propagation-related features, including one vector describing the physical distances between devices based on RTT, and another vector labels an ID for each distance. The distance between smartphones is labeled as "0", while the distances between the first smartphone to every APs are labeled as "-1" and the distances between the second smartphone to every APs are labeled as "1". The IDs are incorporated because we want the model to learn the different types of distances and leverage that information in feature aggregation. The A in the figure represents matrices describing the graph structure. The outputs of the model will be a numerical value that predicts the physical distance between two smartphones.

RTT-GCN is based on GCN, and the dataset is split

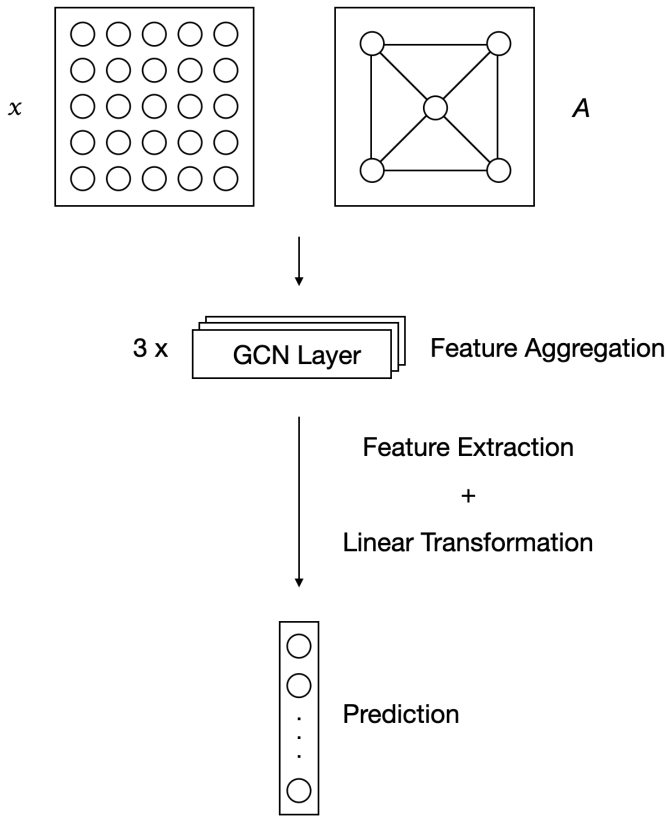

図 3 Network Structure of RTT-GCN

into a training dataset and a testing dataset. In the training process, the input data is fed into three GCN layers after standardization. Then the learnt representation is processed through feature extraction and linear transformations. The output will be optimized according to Mean Squared Error (MSE) loss function and evaluated based on absolute error when compared to the ground truth value.

4. Data Collection Method

In 2016, IEEE 802.11mc standardized the fine tuning measurement (FTM) protocol that allows an AP to measure the round-trip time between it and a wireless device by calculating the time-of-flight of signals. The protocol allows a Wi-Fi-enabled device to send an FTM request to a nearby RTT-capable AP, and the AP will send an acknowledgment back to the device. After several rounds of interchanges, the smartphone will get an estimated distance between them by calculating the time it takes for the signals to travel in between.

If a smartphone sends an FTM request to an AP at t_1, the AP receives it at t_2 and sends an acknowledgement back at t_3, the smartphone receives it at t_4, RTT and corresponding distance can be calculated as follows, where c

denotes the speed of light:

$$RTT = (t_4 - t_1) - (t_3 - t_2) \quad (1)$$

$$Distance = \frac{RTT \cdot c}{2} \quad (2)$$

Devices: The model of APs we plan to use is the **Google** Nest Wi-Fi router. The smartphones we prepare include a Google Pixel 2 (manufactured by **HTC**), a Google Pixel 3 XL, a Google Pixel 4, a Google Pixel 4 XL, and a Google Pixel 5 (all manufactured by **Foxconn**).

Applications: The Android application we use to collect the RTT measurements is modified based on the public *WifiRttScan* App developed by **Google**. While the original app is able to write down RTT measurements to a selected AP in a csv log, we modified it so that it is able to record RTT measurements from all available APs nearby. We use an app based on *ARPose* to collect ground truth location information using images from the camera lenses.

5. Preliminary Experiment

In this study, we conduct a preliminary experiment using simulated data to evaluate the effectiveness of our approach.

5.1 Data simulation

First, we generate random coordinates of two smartphones and six APs within a virtual environment of $25m \times 25m$. Then we calculate the euclidean distances between the coordinates representing the smartphones and the ones representing APs, and add random positive values to simulate noise in reality. The distance between smartphones is regarded as the target for the output of the model. A feature vector describing the classes of the nodes were also generated. Also, an adjacency matrix that corresponds to the graph is generated for each data entry. Based on experiments, we hide the information of the node representing the target distance in all the matrices for the first GCN layer, and also removed some of the redundant edges among nodes, i.e., those corresponding to the relationship among APs, for better prediction accuracy. We generated 10,000 data entries, i.e., data observations of 10,000 different scenarios, for the training dataset and 1,000 data observations for the testing dataset.

5.2 Results & Discussion

The trained model results in an average absolute error of 4.74 m from the ground truth value on the testing dataset. If we consider a naive approach that predicts the distance between smartphones by taking the average of distances in the entire dataset, RTT-GCN achieves predictions that are around 25% better.

Compared to Nakatani et. al.'s [2] study which has an average error of bigger than 3 meters when the actual distance is shorter than 20 meters, the precision of RTT-GCN still needs improvement. However, this is only a preliminary result that leverages only RTT measurements and types of connections. We believe the accuracy of RTT-GCN will be improved if we incorporate other meaningful features from actual data collection as input.

We are considering how to improve the network structure of RTT-GCN. For example, we want to first examine whether there is any information lost or ignored along the convolution layers and linear transformations. Also, our current graph structure only carries information of which smartphone each node corresponds to as a channel in x. We believe it will be helpful to generate an additional graph that gathers information of which smartphone and which AP that each distance corresponds to, and fuse it into the current graph structure to increase its performance.

6. Conclusion

In this paper, we propose a novel method to predict the physical distance between two smartphones using Wi-Fi RTT measurements. To the best of our knowledge, we are the first to apply GCN and leverage line graphs to process the geometric information for distance estimation. The estimated error is 4.74 meters for the testing dataset.

7. Future Works

Currently, the result of RTT-GCN is evaluated using only simulated data. In the future, the first thing we will do is to perform data collection in various real environments. Meanwhile, other valuable data such as RSSI measurements and standard deviations can be acquired and used as additional input features.

After data collection, we will also explore other modules that will contribute to improving the accuracy of RTT-GCN. For example, a time-series module that analyzes the movement trajectory of the smartphone can be potentially helpful. We will also analyze the effects of different combinations of parameters, e.g., by changing the number of GCN layers, size of input and output channels, etc.

謝辞 This work is partially supported by JSPS KAKENHI Grant Number JP21H03428, JP21H05299, JAPAN.

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