Wi-Fi Beacon-Based Localization for Guiding Visually Impaired Persons in Subway Stations

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***Abstract*—Indoor localization is a highly studied topic and many methodologies for indoor localization are showing great results in application domains. However, the practical use of Indoor localization is limited by the elements of the technology. Especially, in Wi-Fi beacon-based localization, a service provider either pre-installs Access Points (APs) or pre-collects the fingerprint data from the existing APs. This process can be highly time-consuming or expensive work. This paper proposes a smartphone application to help the navigation of a visually impaired person in a subway station. The application analyzes fingerprint data with multi-layer perceptron to estimate the user's position and focuses on minimizing pre-data collection for easier and inexpensive service implementation.**

***Index Terms*—Localization, Wi-Fi Beacon, Fingerprint, Neural Network, Multi-layer Perceptron.**

I. Introduction

One of the goals of the public systems operated by a city is to enable all citizens to live above a certain level of life quality. To this end, it is necessary to guarantee the "right of mobility" of visually impaired persons. Nowadays, many efforts are made to supplement the right to travel by improving the accessibility of public transportation services such as subway stations. However, the problem is that installing dedicated APs for indoor navigation systems in public places takes a huge cost for the given numerous subway stations across the country. Therefore, this paper intends to show that a practical navigation service can be established to improve the right to move the visually impaired at a minimum cost with a localization scheme [1].

In order to pursue the minimum cost and procedure, this paper developed an application to improve the process of the existing "Traffic Vulnerable User Service" provided by public transportation organizations in Korea such as KAC (Korea Airport Corporation) and KORAIL (Korea Railroad Corporation). The Application's indoor localization system is based on fingerprint data of public/private APs existing around the station, allowing the reduction of initial implementation cost [2].

II. Implementation

The system of this paper was largely divided into four parts. The first is a user application (A) for "Traffic Vulnerable User Service". The second is a provider application (B). The third is a server (C) that mediates both applications. The fourth is a PyTorch Neural Network Model (PNNM) (D), which infers the location of a user based on Wi-Fi fingerprint data near the user.

TABLE I
Implementation Configuration

Component	Used Open Source
(A) User Application	Android OS
(B) Provider Application	Android OS
(C) Server	Django, AWS LightSail
(D) PyTorch Neural Network Model	PyTorch

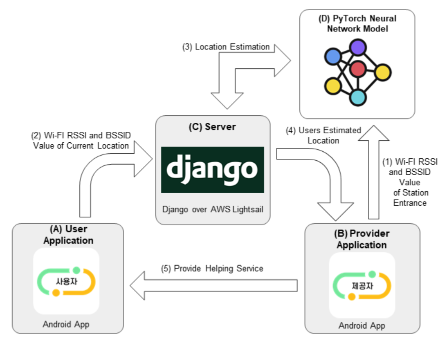

Fig. 1. A Wi-Fi Beacon-based Localization System

Fig. 1 describes the flow of the single cycle of the Wi-Fi-based localization system. In Step (1) of Fig. 1, the transportation service provider transmits fingerprint data of APs collected at each entrance of the subway station to the PNNM. PNNM infers the location of the user based on the Wi-Fi BSSID and RSSI values received from the user in Step (2). In Steps (3) and (4), service providers can find out that the user is requesting help, and the user is currently located at a specific exit of the subway.

Service provider proceeds with service provider registration through A3 to A6 in Fig. 2. In this process, AP scanning of the place where the service is to be provided is performed. In this process, the provider delivers BSSID and RSSI values of neighboring core APs to the server for 10 times at intervals of about 3 seconds for each location. At this time, in order for an AP to be selected as a core AP, both of the following conditions must be satisfied. Firstly, the SSID of the AP should be different from the basic SSID of the mobile hotspot set by

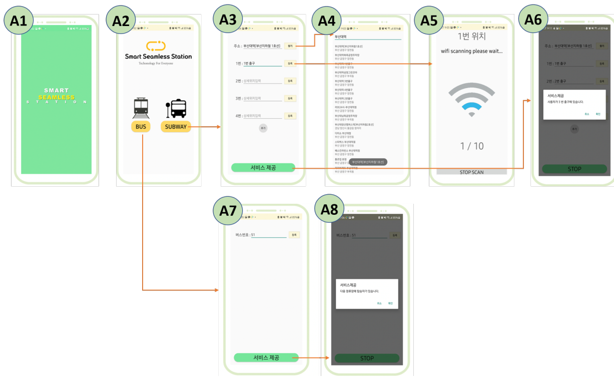

Fig. 2. Provider Application Storyboard

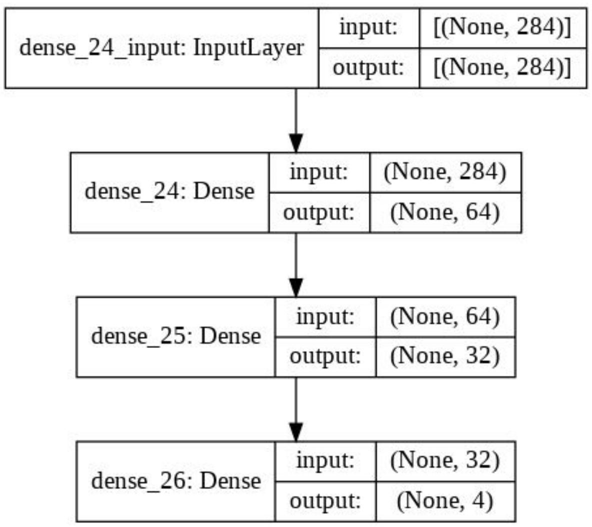

Fig. 3. PyTorch Neural Network Model of Pusan National University Station

the smartphone manufacturer. In the case of Android, the basic SSID of the mobile hotspot starts with "AndroidHotspot". APs with these SSIDs are excluded from the selection because their location is very likely to change in the future. Secondly, in terms of an AP's RSSI value, the top 10 APs with the largest RSSI values among APs recognizable at the current location are selected as core APs. Upon receiving the values of the core APs, the server creates and learns a neural network model for the location and stores the best model. When the user delivers the current AP fingerprint data to the server for indoor positioning, the server puts this value in the best model, infers the user's location, and delivers it to the provider.

III. Performance Evaluation

Fig. 3 represents the structure of a neural network model automatically generated by AP fingerprint data from Pusan National University Station. PNNM's 284 input nodes correspond one-on-one to all core APs collected near the Pusan National University Station, and the four output nodes correspond one-on-one to exits of the Pusan National University Station.

Testing accuracy (train acc) indicates the accuracy of a model's determination for a testing dataset, and testing loss

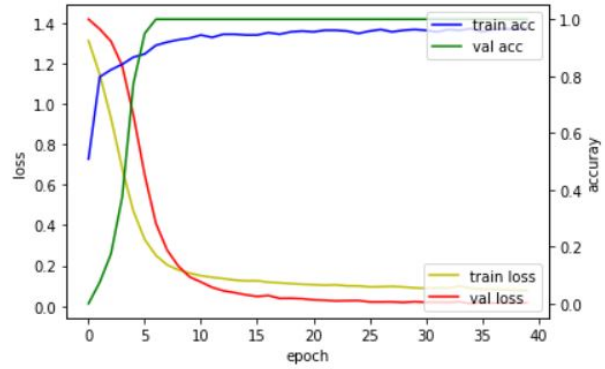

Fig. 4. Training Accuracy over Epoch

(train loss) indicates the difference between the ground truth and estimation for the testing dataset. On the other hand, validation accuracy (val acc) indicates the accuracy of a model's determination for a validation dataset, and validation loss (val loss) indicates the difference between the ground truth and estimation for the validation dataset. Note that the validation dataset is used to avoid overfitting a model during the training of the model. As shown in Fig. 4, the testing accuracy of the 40th epoch was 0.96, so our model could reach a high-level trust. In order to proceed with the learning to that level, AWS LightSail's single GPU instance was used, and the learning time was within 10 to 15 seconds.

IV. Conclusion

In this paper, an application that improves "Traffic Vulnerable User Service" through a simple indoor positioning system was proposed. The applications and systems developed so far cannot keep up with the change of AP fingerprint over time. Therefore, a high-level accuracy can be maintained only by repeating AP scans periodically. As future work, we will reduce the scan frequency by improving the selection algorithm of core APs.

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