2016 International Conference on Indoor Positioning and Indoor Navigation, 4th-7th October 2016

Integrating Wi-Fi and Magnetic Field for Fingerprinting Based Indoor Positioning System

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Abstract— **Smartphone based personal tracking is very important for people to find their destination in large complex buildings (e.g. shopping malls, airports and museums). Such applications are highly demanded in both industries and research organizations. One critical issue for these applications is lack of mature technologies for highly accurate indoor location tracking. In this paper, a new Wi-Fi and magnetic field based smartphone tracking system, named WMLoc, was introduced. The system is a part of a collaborative project between the RMIT University and a famous Australian software company. A number of tracking algorithms such as K nearest neighbor (KNN), artificial neural network (ANN) and back tracing (BT) have been developed or adopted for the system in order to obtain a real-time precise location of the smartphone user. The integration of Wi-Fi and magnetic field includes physical floor analysis, label pattern creation using ANN and BT for enhancing the tracking reliability and improving positioning accuracy. The WMLoc system was tested in two buildings at the RMIT University, Australia. The preliminary results showed that the average root-mean-square (RMS) error of the WMLoc system was less than 2.6 m.**

Keywords—Wi-Fi localization, smartphone based tracking, magnetic, indoor positioning

I. INTRODUCTION

Smartphones nowadays have become the most important information communication tool between users and their surrounding environments. Smartphone based tracking and positioning applications are therefore stimulating extensive research on location based services (LBS) [1]. Among these applications, indoor personal tracking provides crucial services for mobile and pervasive applications from customer shopping behavior retrieving in large shopping malls to navigation during emergency rescue.

Wi-Fi is a standard networking technology and its access points are widely deployed in public areas. In recent years, Wi-Fi has become a default feature of all smartphones. Society has become increasingly dependent on their smartphones as the main source of telecommunication, entertainment, and LBS [2]. According to Donovan's report, Wi-Fi market revenues are forecasted to reach US $12 billion by 2017, a 57% increase over the 2012 revenues [3]. Wi-Fi has been used in 25 percent of homes around the world, and about two billion Wi-Fi devices were sold in 2013 [4]. Various sensors, such as Global Positioning System (GPS) receivers, accelerometers, gyroscopes, digital compasses, cameras, Wi-Fi, and Bluetooth, have been embedded in smartphones for these purposes. Driven by the rapidly increasing demand from the smartphone industry, wireless local area network (WLAN) technologies experienced significant development. Consequently, Wi-Fi and smartphone based indoor tracking and positioning applications has attracted tremendous interests during the past decade both in research and industrial fields. Wi-Fi is becoming so popular as its simplicity and leveraging on the widely available infrastructure without any additional equipment required to smartphone users [5]. However, an indoor environment leads to non-line-of-sight (NLOS) propagation. Wi-Fi based positioning is still facing an inaccuracy problem because of the unstable signals and multi-path interference [6, 7].

Another emerging technology — magnetic is getting more and more popular in recent years. Similar to Wi-Fi, magnetic field based tracking and positioning technology does not require the end users to carry any additional device except a smartphone. The magnetic field even more commonly available everywhere on the earth, and all smartphones nowadays have an embedded magnetometer and free available for collecting magnetic data when needed. Therefore, magnetic field based tracking and positioning technology can be considered as a complementary technique to Wi-Fi in order to improve the estimated positioning accuracy. In fact, many researchers and industrial firms have been working on the integration of Wi-Fi and magnetic field for several years. Products such as IndoorAtlas [8] and Magicol [9] have been used commercially.

Generally there are two popular types of approaches for indoor tracking and positioning: trilateration (or called multi-lateration) and fingerprinting [10-12]. Triangulation approach is based on RSSI or time of receiving the wireless signals and is not accurate for complex environment. Instead, fingerprint is usually performing better in a complex indoor environment. In fact, fingerprinting has been becoming a dominant methodology used for Wi-Fi and magnetic field based tracking, which is also a popular approach for indoor positioning systems using other technologies. The accuracy of fingerprinting based tracking systems depend on the number of Wi-Fi access points (APs) deployed, spatial differentiability, and temporal stability of the radio environment. Many studies have effectively employed wireless networks for indoor localization using RSSI observations based on the fingerprinting technique [13]. Fingerprinting is capable of alleviating some of the problems caused by multipath and NLOS propagation in an indoor environment, whereas it requires a survey of radio frequency

978-1-5090-2425-4/16/$31.00

(RF) signal strength vectors to be made ahead of the system's usage for localization. It stores the location dependent characteristics of a signal recorded at reference points (RPs) in a database in the training phase, and in the location detection phase, pattern matching algorithms are applied to find the best match between the fingerprint of the user and the database, and eventually estimates the position of the user based on better matches.

In this research, a new indoor personal tracking system named WMLoc system is presented. Both Wi-Fi and magnetic technologies are engaged for the system. The fingerprinting approach is used for estimating the user's position. Apart from the usage of the nearest neighbor (NN) and K nearest neighbor (KNN), other algorithms such as artificial neural network (ANN), back tracing (BT) are also integrated in order to improve the positioning accuracy. Floor layout analysis is used for pre-process of the fingerprinting database construction

The rest of the paper is organized as follows. Section 2 presents an overview of the analysis of Wi-Fi and magnetic field signals. Section 3 introduces the main algorithms used for the estimation of the end-user's location. In section 4, the structure and graphical user interface (GUI) of the WMLoc system is described. Finally the testing process of the WMLoc system is addressed, the test results of the WMLoc system are discussed, as well as the future work of the system development is summarized in section 5.

II. Signal Analysis

A. *Wi-Fi signal analysis*

Wi-Fi signals are free available for smartphone based tracking almost everywhere inside buildings. However, Wi-Fi signals fluctuate all the time and seriously reduce the tracking results. One reason of the signal variation is the effect from AP's surrounding environment. Wi-Fi signal can be seriously affected during its propagation by the surrounding facilities such as the walls, floors and other devices. The affected Wi-Fi signal cannot conform to an ideal isotropic sphere. A real Wi-Fi signal map captured from the commercial Ekahau Site SurveyTM system (see Fig. 1) demonstrates this characteristic.

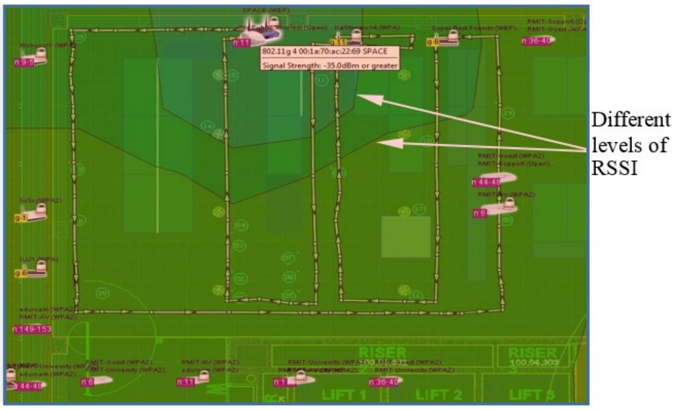


Fig. 1. Map of Wi-Fi signal propagation (tested in the Indoor Positioning Lab, RMIT University)

Among these affecting factors, the physical layout and associated use of patterns is the most important factor being considered, e.g., it is unlikely to detect a user at some places/spaces where people are impossible to be. These "dead-spots" should be removed from the locations of interest.

Another reason of the signal fluctuation is from the signal transmision itself. The received signal strength indication (RSSI) values always vary between different phones, even the phones are of the same model and in the same environment. A simple test indicates these characteristics, in which three smartphones with the same distance to the same AP were used to collect RSSI values. The RSSI value variation can be seen in the test results shown in Fig. 2.

The variation of the signal propagation leads to the uncertainty of Wi-Fi based localization, which is the main drawback of the Wi-Fi based application. In this case, other technologies are often combined with Wi-Fi for improving the perfromance and precision of the tracking system.

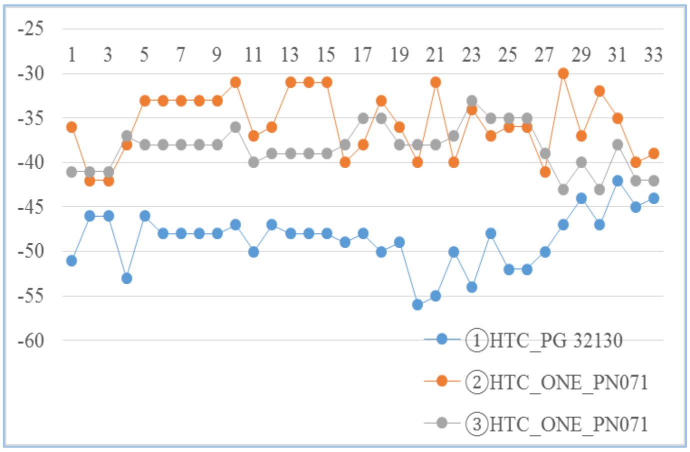
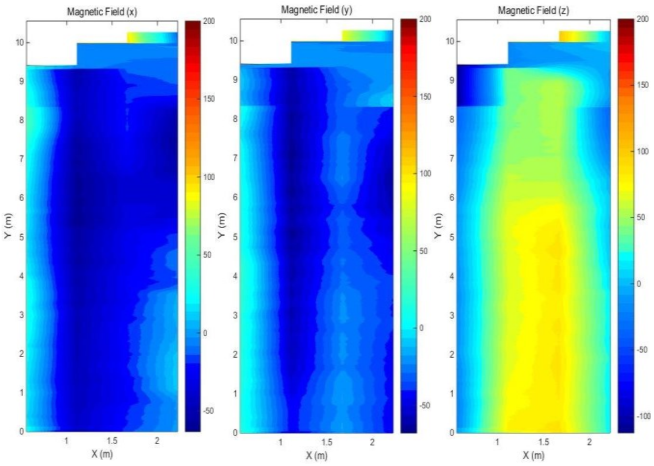


Fig. 2. Comparison of 33 RSSI values received from three smartphones at a 5-second sampling rate

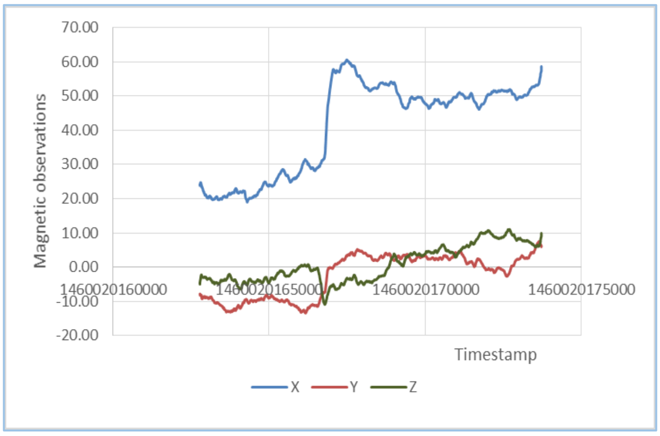
B. *Magnetic field analysis*

The indoor magnetic field combines the geomagnetic field and the fields from ferromagnetic objects. Significant variation of the magnetic field readings are good for implementation of fingerprinting. Fig. 3 shows the magnetic density map captured by a smartphone in a 10 m × 2.5 m indoor area. Fig. 3(a), 3(b) and 3(c) are the magnetic field map from x, y and z respectively. As can be seen, the magnetic field readings from the three axes are all changed significantly while the location varying. Another simple test (see Fig. 4) also showed that the magnetic observation values in x, y and z axes varied greatly when user's walking orientation (along a corridor) changed. However, our previous test results [14] showed that the magnetic field observations in *z* axis are not sensitive enough when user device's height is changed, which indicated that magnetic itself is not capable enough for height (e.g. floor level) detection. In this research, Wi-Fi is selected as a combination technology for solving the height detection problem.

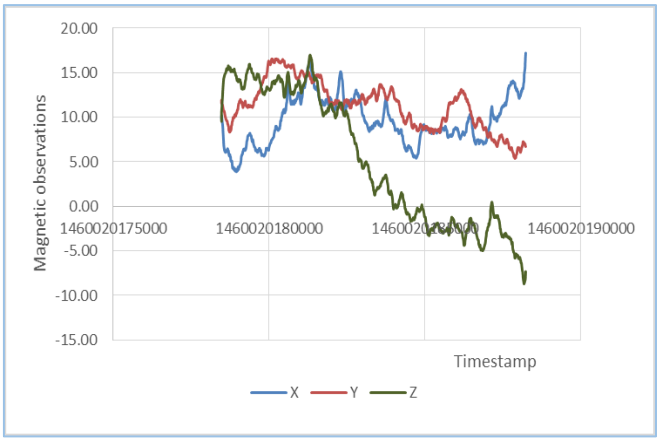


(a) Map in x axis (b) Map in y axis (c) Map in z axis

Fig. 3. Magnetic field maps in different orientations



(a) Moving ahead in a period of about 10 seconds



(b) Returning back (about 10 seconds)

Fig. 4. Magnetic field observation values in x, y and z directions

III. METHODOLOGY

A. Algorithms used for the WMLoc system

A number of algorithms have been used by the WMLoc system for data collection, integration of the magnetic and Wi-Fi signals as well as the real-time user tracking, as listed below:

- Wi-Fi and magnetic based fingerprinting
- Artificial neural network (ANN)
- K nearest neighbour (KNN)
- Low pass and mean filter
- Back tracing (BT) algorithm as an auxiliary approach helping to predict the current location.
- Cell of Origin (CoO)
- Integration of two or more of the above algorithms

More detailed specification on the above algorithms is introduced in the following paragraphs.

B. Methodology

The WMLoc system offers a new perspective to integration of the Wi-Fi and magnetic technologies. As before mentioned, fingerprinting is mainly used as the main approach for the WMLoc system. During the training phase, the magnetic field (mainly the field values in north and east directions) and Wi-Fi RSSI values are collected at each user's location, then the magnetic and Wi-Fi based data are pre-processed and stored in a fingerprinting database (DB). During the real-time location detecting phase, a group of real time data are collected by the user's smartphone, then the data are compared with each group of the data stored in the fingerprinting DB. The WMLoc system exploits the ANN algorithm and combines Wi-Fi RSSI and magnetic field values, plus other algorithms such as BT and knowledge of the real floor map together to facilitate the achievement of real time user location tracking.

In combination with fingerprinting approach, an artificial neural network (ANN) based algorithm was developed as part of the methodology. Recent research has shown an ANN to be capable of pattern recognition [15]. As a result of the combination, a label pattern (also called "machine learning model") was created instead of the normal fingerprinting database during the training phase of the fingerprinting. More specifically, each dataset of the training data, including the location coordinates, 3-axis magnetic observation values and a group of MAC-RSSI values collected at each RP, is used to establish the machine learning model. The training data are used to establish a training model using the theory of ANN. The principle of the training model is described in the diagram in Fig. 5.

First training dataset is used for establishing the regression model by the ANN approach which roughly contains three layers, i.e. input, hidden and output layers. In this project, the input layer is a one-dimensional data (vector) and contains n units $(X_1^1, X_2^1, \dots, X_n^1)$, which is processed by:

$$X_1^2 = g(\theta_{11}^1 X_1^1 + \theta_{21}^1 X_2^1 + \cdots + \theta_{n1}^1 X_n^1)$$
$$\vdots$$
$$X_m^2 = g(\theta_{1m}^1 X_1^1 + \theta_{2m}^1 X_2^1 + \cdots + \theta_{nm}^1 X_n^1) \qquad (1)$$

where θ_{nm}^1 is the regression model's coefficients used for data conversion between adjacent layers; the subscript m for θ denotes the number of the hidden unit; while the superscript (e.g. 1) is the number of layer (i.e. 1 is the input layer, 2 is the output layer); and $g(a)$ denotes the general projection function in all the sub-hidden layers (if there is only one sub-hidden layer, then $g(a) = a$). $X_0^1, X_0^2, \ldots, X_0^j$ are experimental constant values for each layer respectively (they are all assigned to 1.0 in this research). An example of the input vector is as: $[L(L_x, L_y, L_z), M(M_x, M_y, M_z), \sigma, (MAC_1, RSS_1), \ldots, (MAC_n, RSS_n)]$, where L, which includes L_x, L_y, L_z, are the location coordinates in x, y and z directions; M, which includes M_x, M_y, M_z, are the magnetic observation values in x, y and z directions, which need to be converted to the global coordination system [16, 17]; (MAC, RSS) is a pair of the MAC address and RSSI value from a particular access point (AP). σ is the standard deviation of the magnetic observations, which indicates the variation of the magnetic signals. σ can be calculated by (2) and (3).

$$M_{avr} = \frac{1}{n}\sum_{i=1}^{n} M_i \qquad (2)$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_i - M_{avr})} \qquad (3)$$

where $M_i = \sqrt{M_x^2 + M_y^2 + M_z^2}$, M_{avr} is the average value of the total sum-up magnetic observations within a time interval (e.g. 1 second).

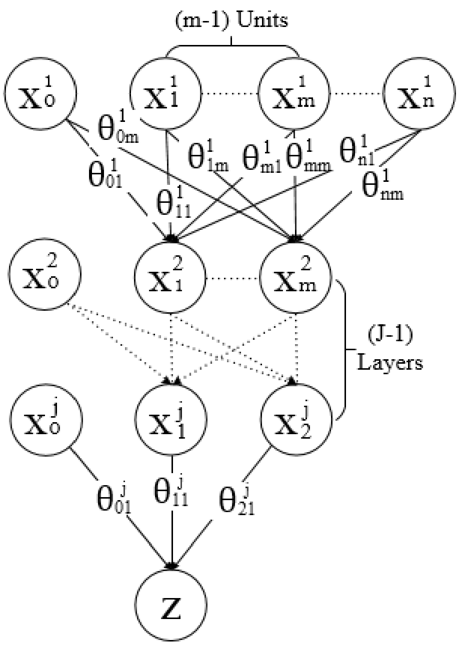


Fig. 5. Principle of the artificial neural network (ANN) algorithm

The input vector is simplified by applying a few algorithms (e.g. constraint of the floor, BT), the amount of its elements are therefore reduced from n to m.

The output vector $(X_1^2, X_2^2, \ldots, X_m^2)$ is generated in the hidden layer, (in this project, only one output vector was selected so far) and the above calculation for solving θ in (1) is recursively processed with a set of randomly selected initial values until a cost function converges with the assistance of a pre-set threshold. The amount of the elements in the output vector is further reduced from m to 2, then to one (i.e. *Z*).

The obtained regression model is then calibrated further by optimizing the scale factor in order to speed up the iteration process as well as the regularization factor (for mitigating both the high variance and over fit of the model) by performing the same procedure repeatedly but using the cross-validation dataset. The calibrated result is the final regression model of the ANN, which is ready for predicting the result of a real-time observation dataset.

The description of other algorithms (e.g. CoO, KNN and BT) can be found in other publications [18-20] and therefore is omitted in this paper.

IV. System Specification

A. *Technical structure*

The WMLoc system is mainly constituted by client and server applications. The server side is responsible for storing floor map and fingerprint data while the client side is responsible for the rest functionalities of the system such as collecting fingerprint or tracking the users.

The floor maps for the test are uploaded to the server side of the WMLoc system through the Google Map Service. The floor-related data such as building name, level number, width and height of the floor map, and floor ID are also stored in the server-side database.

B. *User interface*

The application is running on an Android based device currently. As the WMLoc is a fingerprinting based system, it includes a training phase and a location detecting phase. The user login UI is shown in Fig. 6(a) and the main user tracking UI is shown in Fig. 6(b). The user tracking UI consists of two view areas, i.e. the floor map view area and navigation bar area located at the bottom of the UI. The green lines displayed on the floor map are the paths where the fingerprints were collected.

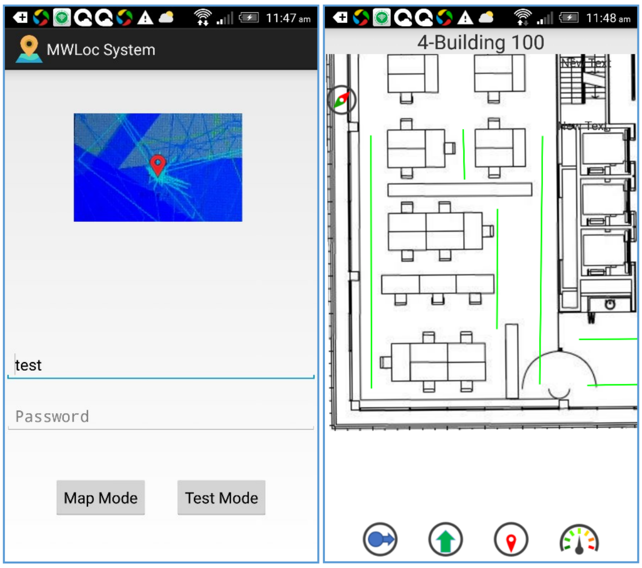
The Four buttons displayed at the bottom of the UI are used for all the operational process control. The functionalities of each button are described below (when button is pressed):

 Starting to draw a collection path or to validate the collected fingerprint data through the corresponding collection path.

 Uploading collected fingerprint data to the server.

 Starting a localization process.


For system configuration set up, such as calibrating the sensor, determining the amount of particle.



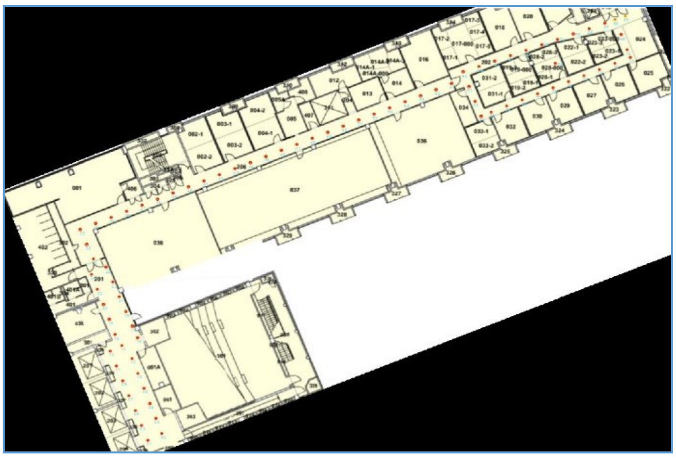
(a)The user login UI (b) The UI for user tracking

Fig. 6. The user interface of the WMLoc system

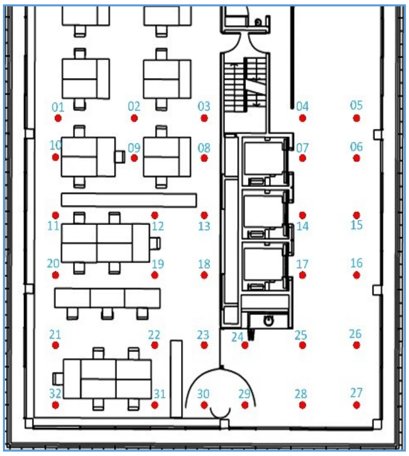
V. Testing and Result Analysis

Two typical testing floor maps for the WMLoc system are listed in Fig. 7. The WMLoc system was tested in both floors. Two smartphones (HTC ONE PN071 and LG G3 D855) were used for the test. A TOSHIBA laptop computer with a Win 7 OS installed, which was used as the server machine for the test.

The testing process was straightforward. Once the "Start Button" was pressed during the tracking process, the smartphone user started to walk along a pre-defined route and then move forward to the end of the route. The system automatically worked out the testing points (the x and y coordinates) for each route. Other information was also collected and processed during the training phase. The true coordinates of each testing point, the label pattern and other data collected during the test can either be found in a file stored in the smartphone or on the server side.



(a) Level 11, Building 14 (about 2500 m^2)



(b) Level 4, Building 100 (about 400 m^2)

Fig. 7. Floor maps and testing points in two Buildings at RMIT University used for the tests of the WMLoc systems

The RMS errors from both testing floors were displayed in Fig. 8. For Building 14, the maximum error is 14.2 m and the minimum error is 0.0 m, the average RMS error is 2.2 m; and for Building 100, the maximum error is 11.6 m and the minimum error is 0.1 m, the average RMS error is 2.6 m. It is reasonable that the average result obtained in Building 14 is more accurate than that from Building 100, as the long corridor based testing environment in Building 14 are more complex than the wider testing areas in Building 100.

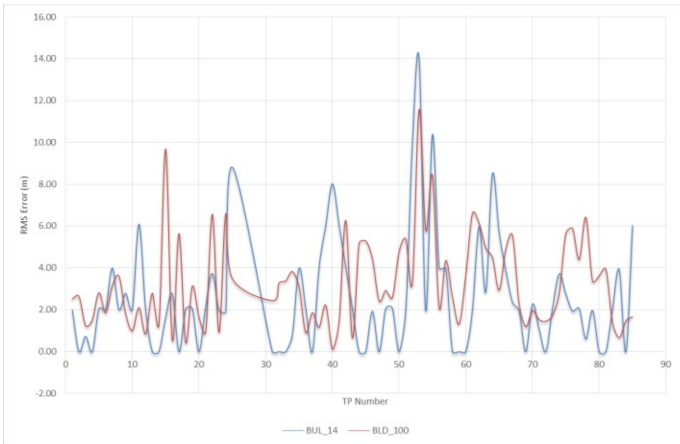


Fig. 8. Results comparison between the two buildings 14 and 100

VI. Conclusion and Future Work

This paper presents a new indoor tracking and positioning system — the WMLoc system, in which a combination of Wi-Fi and magnetic is deployed. While fingerprinting method is used as the main methodology of the system, a number of other algorithms such as ANN, KNN and BT are also integrated and used to consolidate the tracking performance. Our tests results showed that the average RMS accuracy of the system is less than 2.6 m, the integration of these algorithms have demonstrated an obvious improvement on tracking accuracy.

Further development works are expected in order to improve the system performance in terms of tracking response speed and accuracy. More enhancement works are also desirable on how to integrate these algorithms more efficiently in the future.

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