DeepPositioning: Intelligent Fusion of Pervasive Magnetic Field and WiFi Fingerprinting for Smartphone Indoor Localization via Deep Learning

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***Abstract*—Since WiFi has been pervasively available indoor, most smartphone indoor localization systems are based on WiFi fingerprinting although they only give coarse-grained location estimation. In this paper, we propose a novel deep learning-based indoor fingerprinting system (called DeepPositioning), combining Received Signal Strength Indicator (RSSI) of WiFi and pervasive magnetic field to obtain richer fingerprinting. DeepPositioning includes an offline learning phase and an online serving phase. In the offline learning phase, deep learning is utilized to automatically extract rich intrinsic features from a large number of multi-class fingerprints collected using mobile phones. Experimental results demonstrate that deep learning models with the intelligent fusion of pervasive WiFi and magnetic field data can effectively improve smartphone indoor localization compared to existing approaches based on WiFi only.**

Keywords-indoor localization; fingerprinting; WiFi; magnetic field; deep learning; smartphone

I. INTRODUCTION

With the rapid development of wireless communication, Location-based Service (LBS) has gained wide attention from both academia and industry [1]. LBS relies strongly on localization techniques. Unlike outdoor localization with line-of-sight (LOS) transmission paths, indoor localization faces a lot of challenges due to multipath effect, shadowing, fading and delay distortion in radio propagation environment [2]. Although a variety of approaches have been proposed in the literature, there exists no widely accepted solutions that can achieve the desired accuracy at an acceptable cost. To date, fingerprinting-based indoor localization becomes an effective approach due to its low complexity and real-time online process [3].

Fingerprinting based indoor localization consists of two phases: the offline phase and the online phase. The offline phase is mainly for database construction by collecting and pre-processing survey data of pre-established reference positions. In this phase, machine learning methods can be used to extract the core features in the survey data and train the learning model, thus obtaining better localization performance and reducing the computational complexity in the on-line phase. In the online phase, the real-time data sensed by a mobile device is used to estimate its position.

Nowadays, WiFi networks are ubiquitous in public buildings and private residences, such as office blocks, shopping malls, and airports. WiFi information can be exploited to provide rough position estimates without additional costs of special infrastructure. The received signal strength Indicator (RSSI) data is commonly used for fingerprinting by many existing indoor localization systems for its high availability in almost all of mobile devices although RSSI fingerprints are coarse-grained [4]. Compared with RSSI, Channel State Information (CSI) is able to provide more information of the channel. Some indoor localization systems using CSI have been proposed, such as FIFI system [5], PinLoc system [6], and DeepFi system [3]. However, CSI can only be obtained by using some specific WiFi network interface cards (NIC), such as Intel's IWL 5300 and Atheros AR9462.

Besides WiFi network information, the ubiquitous magnetic field information inside a building is available for indoor localization. Similar to Earth's non-constant magnetic field, the magnetic field inside a building can be highly non-uniform [7]. Many buildings have their own, distinguishable magnetic field with small local anomalies. These anomalies of the magnetic field inside a building are nearly static and have sufficient local variability so that they can be utilized as unique magnetic fingerprints [8]. Several indoor localization and navigation systems [9-11] have been proposed to use the geomagnetic field due to its global availability and stability.

In this paper, we aim to utilize ubiquitous WiFi and magnetic field information for smartphone indoor localization. Some papers have proposed to exploit the fusion of magnetic and WiFi signals to achieve significantly improved positioning accuracy for indoor environments. For example, the Magicol system designed a two-pass bidirectional particle filtering process for location estimation with magnetic and WiFi signals [12]. In this paper, we propose a deep learning based indoor localization system called DeepPositioning, using RSSI and magnetic data. DeepPositioning fully exploits intrinsic and rich fingerprints inside a building using general WiFi and magnetic field information. It only needs a mobile phone as the required infrastructure. Today's smartphones are equipped with various sensors such as accelerometers, cameras, magnetometers, and microphones. DeepPositioning is validated with experiments in a representative computer laboratory environment. Our experime

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demonstrate that our deep learning method can extract richer fingerprints through the fusion of magnetic and WiFi data.

II. RELATED WORK

Indoor localization is a challenging task with no universal solution. A variety of techniques have been used, such as Bluetooth [13], ultrasonic and sound techniques [14], visible light [15], motion sensors [16], or even infrared transceivers [17]. Some of these methods can achieve fined-grained indoor localization at the centimeter-level. For example, the Guoguo system [18] [19] utilizes the acoustic signal in the smartphone to implement indoor localization, and the achieved average localization accuracy is about 6~25cm in typical office and classroom environments. However, these methods require extra infrastructure, which is a major obstacle in their widespread applications.

At present, practical smartphone-based indoor localization remains an open problem [19]. Some accurate localization solutions cannot be readily converted for use with smartphones due to various constraints. For the last decade, many approaches have utilized WiFi network for indoor localization. A WiFi-based approach minimizes the system infrastructure cost and does not require any specific device other than the one that connects to the wireless network.

Based on the processing type of WiFi signals, WiFi-based approaches are typically categorized into three groups: (1) Angle of Arrival (AOA) [20]; (2) Time of Arrival (TOA) or Time Difference of Arrival (TDOA) [21]; and (3) fingerprinting approaches [3][5]. Amongst these, fingerprinting based approaches have gained much attention lately. There are two main approaches employed in fingerprinting based approaches: deterministic methods such as RADAR [22] and probabilistic methods such as Horus [4].

Fingerprinting based approaches focus on efficiently comparing the observation value to a pre-recorded database inside the building. In more detail, fingerprinting based approaches consist of two phases: the offline phase and the online phase. In the offline phase, the area is segmented into reference points (RPs). At each RP, survey data, such as RSSI, is collected from the Access Points (APs), whose locations are not necessarily known. The traditional solutions rely on filtering, manual data analysis, and time-consuming parameter tuning to achieve accurate localization. Those solutions are difficult to tune in case of a larger building and a large amount of available data. Machine learning approaches, such as neural networks and support vector machine, can be used to train fingerprints. Deep learning is a recent and powerful machine learning paradigm. Deep learning architectures have the ability to automatically learn features with higher levels of abstractions as well as complex mappings from input to output. At present, several research projects have been launched to use deep learning approach to improve indoor localization accuracy [3][23][24].

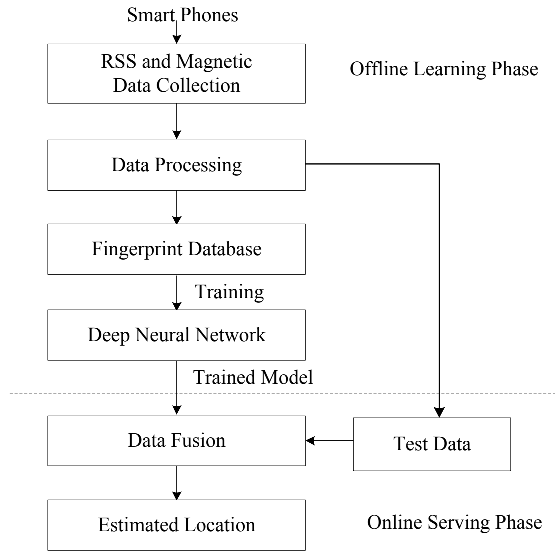

Figure 1. Architecture of the DeepPositioning system.

III. THE DEEPPOSITIONING SYSTEM

A. System Architecture

The architecture of the DeepPositioning system is shown in Fig. 1. DeepPositioning requires no extra infrastructure except existing APs in the building to estimate the unknown location of a mobile device. In addition, it requires no prior knowledge of AP locations, which is often unavailable in commercial or office buildings. Location estimation is conducted through two phases: offline learning phase and online serving phase. In the offline phase, pervasive RSSI and magnetic raw data of all the predetermined RPs are collected at the mobile device. In this phase, a set of RSSI and magnetic values are collected at each RP and transmitted to a localization server. After collecting several fingerprint samples from all RPs, the localization server pre-processes the raw RSSI and magnetic data to meet the requirements of input data in the deep neural network. Weighted training can then be implemented using the datasets. The precise locations of RPs can be used as labels in learning phase. In the online phase, smartphones or other mobile devices collect RSSI and magnetic raw data and request a localization service from the localization server. The localization server pre-processes the collected data using the same algorithm in the offline phase and then lets them flow into deep neural network. An estimation of the unknown location can be calculated using the output results of the neural network.

B. Data Collection and Pre-processing

Almost all smartphones are equipped with a wireless network adapter and various sensors such as accelerometers, cameras, magnetometers, and microphones. It is easy to obtain information of the WiFi networks and from the various sensors in smartphones. These may be used for personal indoor localization.

1) WiFi data: The result of a typical WiFi scan contains names of observed WiFi networks, their MAC addresses, and corresponding signal strengths in dBm. In theory, each WiFi scan contains the signal strength measurements for all of APs available in its vicinity. But in actual implementation, only a subset of total number of networks in the environments are observed in each WiFi scan. To ensure the fingerprint samples are always with the same dimension, we need to define a representation of the lack of measurement for some networks that are not available in a position. Let n be the number of available APs and $R=[r_1, r_2, ..., r_n]$ denote a WiFi scan sample from any RP where r_j $(1 \le j \le n)$ denotes the RSSI value of the j -th AP. R is used as part of input samples of neural network.

2) Magnetic data: The magnetic field is measured producing a three-dimensional vector $m=[m_x, m_y, m_z]$ consisting of three components, in units of μT, of the magnetic density in x, y, and z directions, respectively. Typically, there are two different ways of utilizing the measurement m. One way is to use the norm $\|m\|$, and the other way is to use m directly. $\|m\|$ is a rotation invariant scalar quantity that provides information only about the magnitude of the magnetic field. Better localization performance can be achieved by using m directly when angular deflection of the sensor can be estimated or controlled.

Note that the magnetic vector m obtained from magnetic field sensor in a smartphone is with respect to device coordinates system that changes as the position of the device changes. Although we can control the device rotation in the offline training phase, the test data obtained in the online serving phase is with respect to a moving coordinate system whose basis is unknown. Thus we should find the coordinates of vector m with respect to the world coordinate system. It is acceptable that users are required to try to keep still when requesting the localization service. We can measure accelerometer and magnetic field values simultaneously through the accelerometer and magnetic field sensors in smartphones, and then obtain the rotation matrix R which is the change of basis matrix from the device basis to the world basis. Given any vector m in device coordinate system, the corresponding magnetic vector w in world coordinate system can be obtained by multiplying R with m.

$$w=[w_x, w_y, w_z]=R\cdot[m_x, \mathrm{m}_y, \mathrm{m}_z]^T \quad (1)$$

Fig. 2 shows the mean values of $\|m\|$, w_x, w_y, and w_z in 120 RPs used in our experiments. The first coordinate w_x is a very small value close to zero. w_y and w_z are the coordinates of vector m lying entirely in the North-Sky plane, which retain the variation of magnetic field in different RPs. Thus we use $[w_y, w_z]$ as part of input samples of neural network.

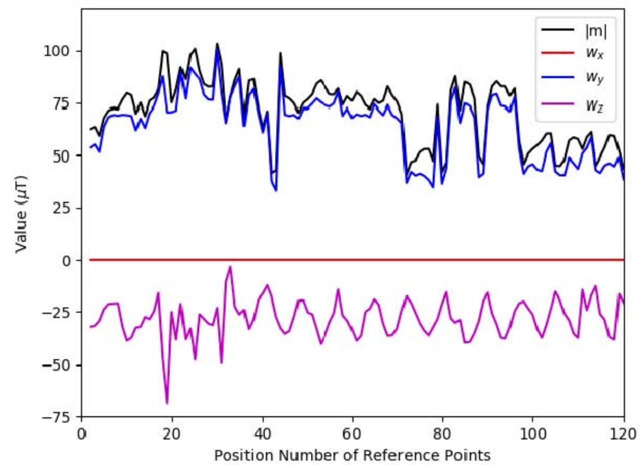

Figure 2. Magnetic field values of reference points in our experiments.

Because the input values should be limited in the range (0, 1) for effective deep learning, we normalize the amplitudes of the RSSI and magnetic values for both the offline and online phases. Since they are different metrics, RSSI measurements and magnetic measurements are scaled independently. For RSSI measurements, we compute the same scaling for all AP measurements instead of scaling measurements for each AP independently.

C. Network Training and Location Estimation

After data collection, the deep learning network is trained by using supervised learning or unsupervised learning, which depends on the type of network. Deep learning architectures such as deep neural network (DNN) and deep belief network (DBN) can be used. Deep learning network can automatically extract instinct features of fingerprint data, significantly different from the traditional methods that directly store survey data. In deep learning network, a hierarchical representation is learned by a cascade of many layers of nonlinear processing units, which can efficiently describe the characteristics of survey data for each location.

We propose to use the most common deep model DNN. DNN is the simplest model of multilayer neural network. The predicted errors propagate backward through layers to adjust the weights of all layers. In this paper, we employ DNN for regression and classification.

DNN with classification typically uses a form of logistic regression in the final layer to convert continuous data into dummy variables normalized into the range of (0, 1), indicating the weight of each class. Assume that the output of the neural network is denoted as $y=[y_1, y_2, ..., y_N]$, where N is the number of RPs and y_i $(1 \le i \le N)$ represents the possibility that the test point belongs to the i -th RP. $L_i=[x_i, y_i]$ is the known physical location information from the i -th RP. The weights of different RPs are calculated as

$$v_i = y_i \Big/ \sum_{j=1}^{N} y_j \tag{2}$$

The position of the test data can be estimated as a weighted average of all RPs, which is given by

$$L = \sum_{i=1}^{N} (v_i \times L_i) \tag{3}$$

DNN with regression maps one set of continuous inputs to another set of continuous outputs. Let $y = [y_1, y_2]$ denote the output of the neural network, where y_1 and y_2 represent the estimated coordinates in two-dimensional space, respectively.

Additionally, stacked autoencoders can also be used as part of the deep network to learn the reduced representation of the original data during unsupervised training [24]. At first, the encoder-decoder pair is trained to achieve the output information same as its input. When the unsupervised training is finished, the decoder part of network is disconnected and a few fully-connected layers for regression or classification are connected to the output of encoder. During the subsequent supervised learning phase, the weights in whole network are modified to create a final system.

IV. Experiment Vailidation

A. Experiment Methodology

DeepPositioning is evaluated through practical experiments. The experiment testbed only need a smartphone. The smartphone we use is a Huawei MT7-TL00 with Android 6.0 system. A Java application runs in the smartphone to perform the data collection process. This process consists of taking readings of the WiFi signal strengths and data from other sensors in the device. The data is associated with a user-provided location and written to a text file on the device, which can be pulled from the device later for analysis.

Experiments were performed in room 4-406, College of Engineering building at the University of Florida. The area size is 13.4m×6.4m. We divided the environment uniformly and selected 120 reference locations based on the existing aluminium alloy grate installed close to the ceiling. The average distance between adjacent reference points is 0.6 m in both X and Y axis. The detailed layout and division are shown in Fig. 3. The room is a computer laboratory and is divided into many cubicles, as shown in Fig. 4. There are many metal desks and computers, forming a complex radio propagation environment and magnetic field.

The data collection process was a little different in training and testing phases. In the training phase, we continuously collect 120-130 fingerprint samples at each RP and the measurement lasts for 5 minutes. In the test phase, we only collect about 30 samples to estimate position considering the practical application scene. A smartphone was held by hand at the same height and placed in front of data collector's chest with a distance of about 0.3 m. The daily walking pattern of people were imitated, such as walking through the laboratory entrance, heading down the aisle, getting up from or sitting down on a station.

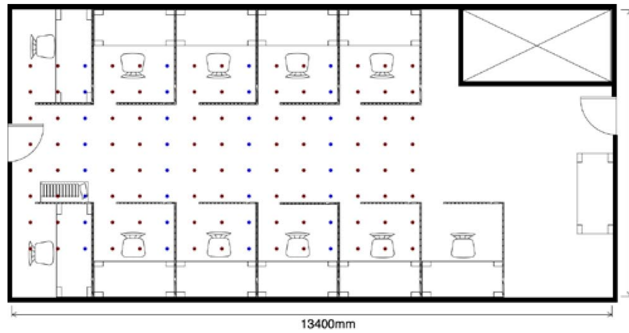

Figure 3. Position points layout of the experiment environment.


Figure 4. Photo of the experiment environment.

Since DeepPositioning explores coarse RSSI values in WiFi networks, APs installed in the building are utilized as many as possible. In our experiment, RSSI data collected from 242 different APs with unknown locations are used, and the lack of signal strength measurement is set to -110 dBm, a signal value weaker than the weakest signal ever received in the dataset.

The accelerometer and magnetic field were measured in the device coordinate system. As stated in Section III, magnetic measurements were converted to coordinates with respect to the world coordinate system. We chose the two values of y and z coordinates as part of fingerprint sample. Therefore, a single fingerprint sample in our experiments consists of 242 attributes corresponding to signal strengths from 242 APs, and y and z magnetic values in fixed world basis. The number of available WiFi signals will vary depending on where the localization system is deployed.

To evaluate the effect of different datasets, we chose 2 different datasets: DS-1 and DS-2, as presented in Table I. In DS-1, the training set includes all of 120 RPs and testing set includes 20 extra positions that were randomly selected. So the distance between two adjacent training spots is 0.6m in x and y axis, respectively. In DS-2, 120 RPs are divided into

TABLE I. TWO DIFFERENT DATASETS

Dataset	Training Set	Testing Set
DS-1	120	20
DS-2	88	32

TABLE II. ARCHITECTURES OF DIFFERENT DEEP NEURAL NETWORKS

DNN	H-Layer 1	H-Layer 2	H-Layer 3	O-Layer 1
4- cls	256	128	128	120
4-aut-reg	256	128	64	2
4- reg	256	128	64	2
3-reg	256	128	None	2

88 training positions and 32 test positions. As shown in Fig. 3, the red and blue spots represent RPs in training set and testing set, respectively. In this case, the distance between two adjacent training spots is 0.6m or 1.2m in x axis.

1) Effect of the Different Deep Neural Networks: In order to evaluate the effect of different deep neural networks on localization performance, we design a specific experiment by using four different DNNs with DS-1. As shown in Table II, 4-reg DNN has three hidden layers and one regression output layer. 4-cls DNN has three hidden layers and one classification output layer. 3-reg DNN has two hidden layers and one regression output layer. Although 4-aut-reg DNN has the same network architecture as 4-reg DNN, its first three hidden layers are stacked autoencoders that are pre-trained in an encoder-decoder pair to learn the reduced representation of the original data during unsupervised training. A fully-connected layer for regression is then connected to the output of encoder and a supervised learning phase is performed subsequently to modify the weights in whole network.

The mean and standard deviation of the location errors in X axis, Y axis, and distance are presented in Table III, respectively. As we can see from this table, deep neural networks with different network architecture and training method have different performance with the same dataset in indoor localization. Among all four DNNs in our experiments, 4-reg DNN outperforms the other three DNNs. The mean errors of 4-reg DNN in X axis, Y axis, and distance are about 1.10, 0.75 and 1.46 meters across 20 additional test points, respectively. The latter three DNNs have degraded performance and they have mean distance errors of 1.73, 1.88, and 1.94 meters respectively. In addition, all the cases have bigger errors in X axis than in Y axis due to the shape of experiment environment.

Fig. 5 presents the cumulative distribution function (CDF) of distance errors with the four DNNs. In 4-reg DNN case, about 60% of the test samples have an error under 1.5 meters, and over 78% of the test samples can achieve an error under 2.0 meters, which is the most accurate one among the four DNNs. By contrast, in 3-reg DNN case, only about 40% and 54% of the test samples can achieve an error under 1.5 and 2.0 meters, respectively.

TABLE III. MEAN ABSOLUTE ERROR FOR DIFFERENT DNNS WITH DS-1

DNN		Mean Error (m)	Std. Dev. (m)
4- reg	X	1.1035	1.0484
	Y	0.7487	0.6483
	Dis.	1.4551	1.0866
4-aut-reg	X	1.3455	0.9540
	Y	0.8670	0.6480
	Dis.	1.7270	0.9537
4- cls	X	1.2040	1.1588
	Y	1.1165	0.8701
	Dis.	1.8846	1.1153
3-reg	X	1.1857	0.9282
	Y	1.2192	0.7850
	Dis.	1.9442	0.9185

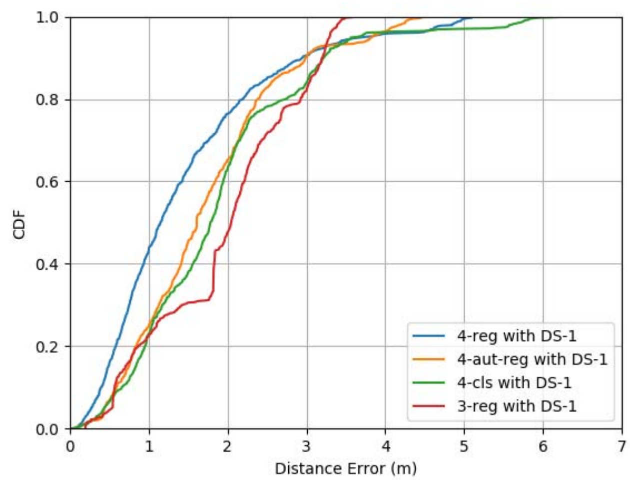

Figure 5. CDF of localization errors of four DNNs with DS-1.

It is shown that the performance of deep learning based indoor localization has a close relationship with the deep network architecture and training strategy. In the concrete implementation process, we should give more concern to choosing network architecture and training strategy according to the amounts of the APs, RPs, and datasets.

2) Effect of the Training Grid Size: In order to evaluate the effect of the training grid size to the performance of DeepPositioning, we study the performance comparasion of DeepPositioning with two different datasets: DS-1 and DS-2. In DS-1, the distance between two adjacent training spots is 0.6m in X and Y axis. In DS-2, the distance between two adjacent training spots is 0.6m or 1.2m in x axis and 0.6m in

TABLE IV. MEAN ABSOLUTE ERROR FOR DEEPPOSITIONING WITH TWO DIFFERENT DATASETS.

		DS-1		DS-2	
		Mean error (m)	***Std. dev. (m)***	***Mean error (m)***	***Std. dev. (m)***
4-reg	X	1.1035	1.0484	1.3816	1.1969
	Y	0.7487	0.6483	0.7925	0.6532
	Dis.	1.4551	1.0866	1.7172	1.2030
4-aut-reg	X	1.3455	0.9540	1.2483	1.1338
	Y	0.8670	0.6480	1.0653	0.8384
	Dis.	1.7270	0.9537	1.9977	1.0546

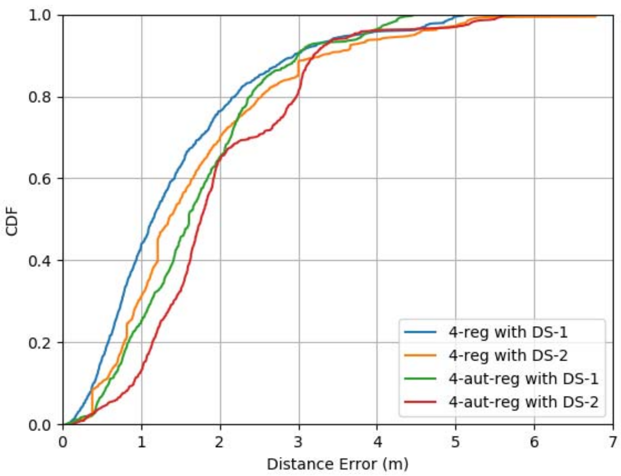

Figure 6. CDF of localization errors of DeepPositioning with two datasets.

y axis. The amount of training reference points in DS-2 is about two-thirds of the amount of training reference points in DS-1. We chose 4-reg DNN and 4-aut-reg DNN, i.e., 4-layer deep neural networks with regression.

Table IV presents the mean and standard deviation of location errors in X axis, Y axis, and distance, respectively. For both 4-reg DNN and 4-aut-reg DNN, they have degraded performances with DS-2 compared to with DS-1. With DS-2, the 4-reg DNN and 4-aut-reg DNN can still achieve 1.72 and 2.0 meters of the mean distance error. Fig. 6 presents the CDF of distance errors with two different datasets. In DS-2 case, 4-reg DNN can achieve an distance error under 1.5 and 2.0 meters for 56% and 71% of the test samples, respectively. 4-aut-reg DNN can achieve an distance error under 1.5 and 2.0 meters for 34% and 65% of the test samples, respectively.

3) Effect of the Fusion of Magnetic Field and WiFi: In order to evaluate the performance of the fusion of magnetic field with WiFi in indoor localization system, we compare the following two cases: DeepPositioning and Wifi only(termed as wifi-only). For a fair comparison, the two cases use the same deep network architecture as 4-reg DNN, differing only in the dimension of input samples. In wifi-only case, an input sample is a 242-dimension WiFi data in our experiment.

TABLE V. MEAN ABSOLUTE ERROR FOR DEEPPOSITIONING AND WIFI-ONLY

		Mean Error (m)	Std. Dev. (m)
DeepPositioning (DS-1)	X	1.1035	1.0484
	Y	0.7487	0.6483
	Dis.	1.4551	1.0866
wifi-only (DS-1)	X	1.6566	1.1139
	Y	1.0186	0.6923
	Dis.	2.1742	0.9271
wifi-only (DS-2)	X	1.8838	1.2800
	Y	1.1687	0.8101
	Dis.	2.3878	1.2279

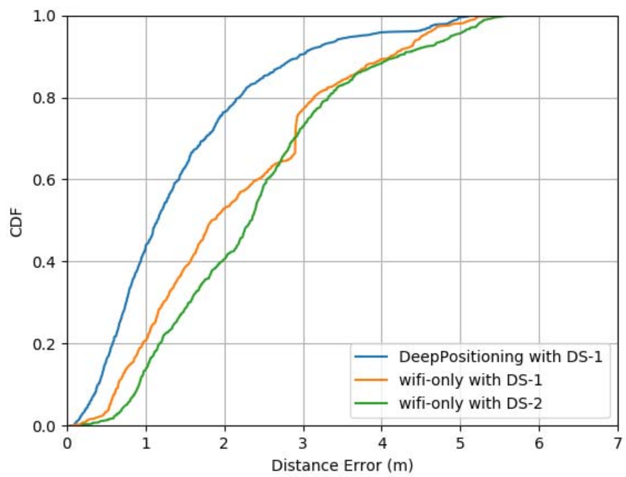

Figure 7. CDF of localization errors of DeepPositioning and wifi-only.

The mean and standard deviation of location errors in X axis, Y axis, and distance are presented in Table V, respectively. The performance of DeepPositioning outperforms the wifi-only case with both datasets in the complex computer laboratory. The wifi-only case can only achieve 2.17 and 2.39 meters of the mean distance error with DS-1 and DS-2, respectively. In addition, both DeepPositioning and wifi-only cases have bigger errors in X axis than in Y axis due to the shape of experiment environment.

Fig. 7 presents the CDF of distance errors with the DeepPositioning and wifi-only cases. The wifi-only case can have a 1.0, 1.5, and 2.0 meters distance error for about 20%, 40%, and 52% of the test samples respectively with DS-1, and for about 16%, 30%, and 41% of the test samples respectively with DS-2. By exploiting the diversity of the magnetic field between adjacent reference points using deep learning model, DeepPositioning proposed in this paper achieves a 30% improvement over the wifi-only case.

V. Conclusion

We proposed a deep learning based indoor fingerprinting scheme DeepPositioning, using the deep neural fusion of magnetic field and WiFi field. DeepPositioning was implemented and validated in the real-world laboratory scenario. Experimental results showed that deep network models combining magnetic field and WiFi fingerprintings improved indoor localization accuracy. Although the training phase of DeepPositioning was computationally intensive, the testing phase is fast and suitable for real-time indoor localization on a mobile device. However, the performance of DeepPositioning has a close relationship with numbers of APs, RPs, and labeled samples in training datasets. In addition, dynamic environments caused by various factors, such as dynamic leaving and joining of APs during online stage, may significantly affect the localization performance. In the future work, we plan to investigate semi-supervised and reinforcement learning algorithms to address these dilemmas.

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References

[1] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 37, no. 6, pp. 1067–1080, 2007.

[2] X. Wang, S. Mao, S. Pandey, and P. Agrawal, "CA2T: Cooperative antenna arrays technique for pinpoint indoor localization," in Proc. MobiSPC 2014, Niagara Falls, Canada, Aug. 2014, pp. 392–399.

[3] X. Wang, L. Gao, S. Mao, and S. Pandey, "Csi-based fingerprinting for indoor localization: A deep learning approach," IEEE Transactions on Vehicular Technology, vol. 66, no. 1, pp. 763-776, 2017.

[4] M. Youssef and A. Agrawala, "The Horus WLAN location determination system," in Proc. ACM MobiSys'05, Seattle, WA, June 2005, pp. 205– 218.

[5] J. Xiao, K. Wu., Y. Yi, and L. Ni, "FIFS: Fine-grained indoor finger-printing system," in Proc. IEEE ICCCN' 12, Munich, Germany, Aug. 2012, pp. 1–7.

[6] S. Sen, B. Radunovic, R. R. Choudhury, and T. Minka, "You are facing the Mona Lisa: Spot localization using PHY layer information," in Proc. ACM MobiSys'12, Low Wood Bay, Lake District, United Kingdom, June 2012, pp. 183–196.

[7] J. Haverinen and A. Kemppainen, "Global indoor self-localization based on the ambient magnetic field," Robot. Auton. Syst., vol. 57, no. 10, pp. 1028–1035, Oct. 2009.

[8] B. Gozick, K. Subbu, R. Dantu, and T. Maeshiro, "Magnetic maps for indoor navigation," IEEE transactions on Instrumentation and Measurement, vol. 60, no. 12, pp. 3883–3891, dec. 2011.

[9] X. Jiang, C. -J. M. Liang, K. Chen, B. Zhang, J. Hsu, J. Liu, B. Cao, and F. Zhao, "Design and Evaluation of a Wireless Magnetic-based Proximity Detection Platform for Indoor Applications, " In ACM IPSN, 2012.

[10] K. P. Subbu, B. Gozick, and R. Dantu, "Locateme: Magnetic-Fields-Based Indoor Localization using Smart-phones," ACM Trans. Intelligent Systems and Technology (TIST), vol. 4, no. 4, Article 73, 2013.

[11] Y. Shu, G. S. Kang, T. He, and J. Chen, "Last-mile navigation using smartphones," in Proc. ACM Mobicom, pp. 512–524, 2015.

[12] Y. Shu, C. Bo, G. Shen, C. Zhao, L. Li, and F. Zhao, "Magicol: Indoor Localization Using Pervasive Magnetic Field and Opportunistic WiFi Sensing," IEEE Journal on Selected Areas in Communications, vol. 33, no. 7, pp. 1443–1457, July 2015.

[13] U. Bandara, M. Hasegawa, M. Inoue, H. Morikawa, and T. Aoyama, "Design and implementation of a bluetooth signal strength based location sensing system," in 2004 IEEE Radio and Wireless Conference, Sep. 2004, pp. 319–322.

[14] F. Ijaz, H. K. Yang, A. Ahmad, and C. Lee, "Indoor positioning: A review of indoor ultrasonic positioning systems," in 15th International Conference on Advanced Communication Technology, Jan. 2013, pp. 1146–1150.

[15] Y. -S. Kuo, P. Pannuto, K. -J. Hsiao, and P. Dutta, "Luxapose: Indoor positioning with mobile phones and visible light," in Proc. of the 20th Annual International Conference on Mobile Computing and Networking, Sep. 2014, pp. 447–458.

[16] A. T. Mariakakis, S. Sen, J. Lee, and K.-H. Kim, "SAIL: Single access point-based indoor localization," in Proc. of the 12th Annual International Conference on Mobile Systems, Applications, and Services, Jun. 2014, pp. 315–328.

[17] R. Want, A. Hopper, V. Falcao, and J. Gibbons, "The active badge location system," ACM Transactions on Information Systems, vol. 10, no. 1, pp. 91–102, 1992.

[18] K. Liu, X. Liu, and X. Li, "Guoguo: Enabling Fine-grained Indoor Localization via Smartphone," in Proc. of the 11th ACM International Conference on Mobile Systems, Applications, and Services (MobiSys), 2013, pp. 235–248.

[19] K. Liu, X. Liu, and X. Li, "Guoguo: Enabling Fine-grained Smartphone Localization via Acoustic Anchors," IEEE Transactions on Mobile Computing (TMC), vol. 15, no. 5, pp. 1144–1156, 2015.

[20] M. Kotaru, K. Joshi, D. Bharadia, and S. Katti, "SpotFi: Decimeter level localization using WiFi," in SIGCOMM Computer Commununications Revision, Aug. 2015, pp. 269–282.

[21] J. Xiong, K. Sundaresan, and K. Jamieson, "ToneTrack: Leveraging frequency-agile radios for time-based indoor wireless localiza- tion," in Proc. of the 21st Annual International Conference on Mobile Computing and Networking, Sep. 2015, pp. 537–549.

[22] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in IEEE International Conference on Computer Communications, 2000, pp. 775–784.

[23] J. Li, Y. Li, X. Ji, "A novel method of Wi-Fi indoor localization based on channel state information," in Proc. of the 8th International Conference on Wireless Communications & Signal Processing (WCSP), 2016, pp. 1–5.

[24] M. Nowicki and J. Wietrzykowski, "Low-effort place recognition with WiFi fingerprints using deep learning," in Proc. of International Conference Automation, Springer, Cham, 2017, pp. 575–584.