# Indoor Robot Localization with WiFi Signal and Convolutional Neural Networks and Recursive Bayesian Estimation

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***Abstract*— This paper presents a robot localization system with WiFi signal where a Deep Learning framework utilized to fully exploit the information from signal maps of various Access Points (AP) available in an environment. Similar to conventional systems relying on the fingerprinting technique, the system is consisted of two stages: data acquisition and learning (offline), and localization (online). In offline stage, the signal maps for various AP's are constructed via Received Signal Strength (RSS) information and learned by a Convolutional Neural Network, whereas the online stage contains the proposed localization method based on an information fusion technique. *Add some result once get it***

## I. INTRODUCTION

Since WiFi has become ubiquitious, it started being utilized in different applications varying from customer tracking indoors to robot localization. However it is available, the information can be extracted from is prone to (suffers from) being sparse and severely effected by infrasracture of environments where WiFi based systems are deployed. Amongst all the applications that WiFi signal can be used, localization is a problem where it is required to have higher level of success in localization accuracy and shorter localization time. *The main contributions of this paper is that the proposed technique can handle sparse, noisy RSS measurements acquired from the off-the-shelf AP's under LoS and NLoS situations, while achieving comparable localization accuracy to thes state-of-the-art methods.*

The success of the systems relying on the WiFi signal, in general, suffers from the phenomenon called Multipath Effect where the AP is not in the direct line of sight and the EM waves from the AP where the received signal is propagated through non-line-of-sight, i.e. concrete and glass walls. Although there is some effort to either model or estimate the Multipath Effect to componsate its effects on the systems [1], it is still an open problem in the field in order to achieve the same level of success. *The proposed system can inherently handle multipath effect, since machine not only can reduce complexity of overall design of the system but also can generalize from the data.*

Another problem with the WiFi signal which makes it difficult to employ it as the main information source is that the signal acquired is not reliable. Figure 1 shows the acquired RSS information acquired with stationary client from the AP's both line-of-sight and non-line-of-sight positions in time. The figure clearly depicts that even for stationary clients, WiFi information #*gotta mention that deviation makes it not reliable*. To be able to extract relatively reliable information, some hardware and software changes proposed to incorporate Channel State Information (CSI) provided by Orthogonal Frequency-Division Multiplexing (OFDM) forming WiFi protocol. As [2] suggests/proves, the CSI information provides significantly reliable information. However, to be able to acquire CSI information, a specific type of NIC should be used with a specific type of firmware. This makes it hard to deploy proposed system on Embedded-devices, IoT's and robotic systems., *while the proposed system can be deployed to almost-any arbitrary system thanks to the simplicity of the design.*

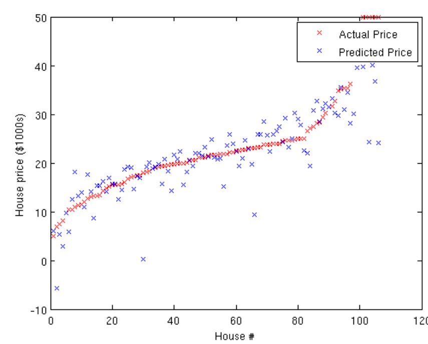


Fig. 1. Inductance of oscillation winding on amorphous magnetic core versus DC bias magnetic field

The paper is organized as follows. The following section reviews the literature regarding robot localization with WiFi signal. In Sec. III, we formalize the problem. Section IV thoroughly explains the proposed system. The experimentation and the results are in Sec. V. We outline our observation and conclusions in the final section.

## II. RELATED WORK

### A. Indoor Localization Based on Fingerprinting

Surveys: [3–5]. UnLoc [6]: zero supervising, no training; heavily depends on landmark extraction and dead reckoning. (mobile device)

Walkie-Markie [7]: spatial-pattern

Particle filter [8]: PF, dead reckoning

LiFS [9]: no radio map required heavily depends on multiresolution mapping.

Zee [10]: off-the-shelf hw, crowdsourcing

ArrayTrack [11]: One of the best

SpotFi [12]: One of the best

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### B. *Indoor Localization with Machine Learning*

kNN: [5]
Neural networks: [13]
SVM: [14]
Deep-Fi [15]: Deep learning

## III. PROBLEM FORMULATION

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## IV. SYSTEM DESCRIPTION

### A. *Offline Stage*

#### 1) *Data Acquisition:*

#### 2) *Training:*

### B. *Online Stage*

#### 1) *Inference:*

#### 2) *Information Fusion:* .

## V. EXPERIMENTATION

### A. *Experimental Setup*

#### 1) *Hardware:*

#### 2) *Software:*

### B. *Results*

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## VI. CONCLUSIONS

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Turkish Government and stuff

## REFERENCES

[1] X. Cai, X. Li, R. Yuan, and Y. Hei, "Identification and mitigation of nlos based on channel state information for indoor wifi localization," in Wireless Communications & Signal Processing (WCSP), 2015 International Conference on. IEEE, 2015, pp. 1–5.

[2] L. Gao, "Channel state information fingerprinting based indoor localization: a deep learning approach," Ph.D. dissertation, Auburn University, 2015.

[3] S. He and S.-H. G. Chan, "Wi-fi fingerprint-based indoor positioning: Recent advances and comparisons," IEEE Communications Surveys & Tutorials, vol. 18, no. 1, pp. 466–490, 2016.

[4] A. M. Hossain and W.-S. Soh, "A survey of calibration-free indoor positioning systems," Computer Communications, vol. 66, pp. 1–13, 2015.

[5] 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.

[6] H. Wang, S. Sen, A. Elgohary, M. Farid, M. Youssef, and R. R. Choudhury, "No need to war-drive: unsupervised indoor localization," in Proceedings of the 10th international conference on Mobile systems, applications, and services. ACM, 2012, pp. 197–210.

[7] G. Shen, Z. Chen, P. Zhang, T. Moscibroda, and Y. Zhang, "Walkie-markie: indoor pathway mapping made easy," in Proceedings of the 10th USENIX conference on Networked Systems Design and Implementation. USENIX Association, 2013, pp. 85–98.

[8] J. Biswas and M. M. Veloso, "Wifi localization and navigation for autonomous indoor mobile robots," 2010.

[9] Z. Yang, C. Wu, and Y. Liu, "Locating in fingerprint space: wireless indoor localization with little human intervention," in Proceedings of the 18th annual international conference on Mobile computing and networking. ACM, 2012, pp. 269–280.

[10] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen, "Zee: zero-effort crowdsourcing for indoor localization," in Proceedings of the 18th annual international conference on Mobile computing and networking. ACM, 2012, pp. 293–304.

[11] J. Xiong and K. Jamieson, "Arraytrack: a fine-grained indoor location system," in Presented as part of the 10th USENIX Symposium on Networked Systems Design and Implementation (NSDI 13), 2013, pp. 71–84.

[12] M. Kotaru, K. Joshi, D. Bharadia, and S. Katti, "Spotfi: Decimeter level localization using wifi," in ACM SIGCOMM Computer Communication Review, vol. 45, no. 4. ACM, 2015, pp. 269–282.

[13] S. Dayekh, "Cooperative localization in mines using fingerprinting and neural networks," Ph.D. dissertation, Université du Québec à en Abitibi-Témiscamingue, 2010.

[14] Z.-l. Wu, C.-h. Li, J. K.-Y. Ng, and K. R. ph Leung, "Location estimation via support vector regression," IEEE Transactions on mobile computing, vol. 6, no. 3, pp. 311–321, 2007.

[15] X. Wang, L. Gao, S. Mao, and S. Pandey, "Csi-based fingerprinting for indoor localization: A deep learning approach," 2016.