A Multifrequency Multistage Indoor Localization Based on Gated Recurrent Units

Murat Ambarkutuk
Mechanical Engineering Department,
Virginia Polytechnic Institute and State University,
Blacksburg, Virginia, USA Email:murata@vt.edu

Tomonari Furukawa
Mechanical Engineering Department,
Virginia Polytechnic Institute and State University,
Blacksburg, Virginia, USA Email: tomonari@vt.edu

Abstract*—This paper presents a multifrequency and multistage indoor robot localization system based on fingerprinting. The proposed system relies on a 900 MHz Long Range Radio (LoRa) along with 2.4 GHz Wireless Fidelity (WiFi) and Bluetooth (BT) networks. By exploiting different propagation characteristics of different Radio Frequency (RF) signal wave within a Gated Recurrent Unit (GRU) framework, Received Signal Strength (RSS) measurements are used for indoor localization purposes. Similar to conventional fingerprinting systems, 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 RSS information and path loss exponent is learned by a network consisted of GRU, whereas the online stage contains an information fusion based localization method. *Add some result once get it

I. Introduction

The radio waves .. Since Radio Frequency (RF) 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, robot 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 in which 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 under NLoS observations. *The proposed system can inherently handle multipath effect, since machine not only can reduce complexity of overall design of the system but also can capture deeper information from the radio maps.*

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, the RSSI readings greatly deviates from the mean in time. 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.*

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

II. Fundamentals of Radio Wave Propagation and Indoor Localization

The relationship between transmitted P_t and received power P_r occurred between ideal antennas in an empty space with a distance d separation is characterized by Friis' Free Space Equation given below [3].

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi d)^2} \tag{1}$$

where $P_r(d)$ and P_t denote received, and transmitted power in Watts, respectively. G_t and G_r are uniteless gains of transmitter, and receiver antenna while λ and d denote wavelength and the seperation between two antennas in meters, respectively.

$$P_r^+(d) = P_t^+ + 10\log G_t G_r + 20\log\lambda - 20\log d - 20\log 4\pi \tag{2}$$

Since the received power is miniscule level, Equation (2) represents Friis' equation in dBm level. $P_r^+(d)$ and P_t^+ represent received and transmitted powers decibel scale. However, Friis' equation does not hold true for the distance $d = 0$. Thus, received power generally denoted relative to a reference point d_0 with a known corresponding received power.

$$P_r^+(d) = P_r^+(d_0) + 20 \log \frac{d_0}{d} \tag{3}$$

Path loss models the difference between received and transmitted power in decibel scale as positive gain. Equation (4) represents path loss relative to a reference point.

$$\overline{PL}(d) = \overline{PL}(d_0) + 10n \log \frac{d}{d_0} \tag{4}$$

where n is the path loss exponent and varies depending on the environment. Please note $n = 2$ for empty space.

A. Indoor Localization Based on Fingerprinting

Fingerprinting-based systems are often had been surveyed many times [4] with different scopes. Zee [5]: off-the-shelf hw, crowdsourcing Many of the previous systems employ spatial pattern of the fingerprints, while others use temporal pattern displayed by AP's. UnLoc [6] is an examplary instance falling into the former category. The system aims for incorporating hard-constraints of the environment, namely, elevators, stairs, entrances, and the change in the fingerprint patterns; for instance, a significant drop of signal level of a specific AP.

Particle filter [7]: PF, dead reckoning

Zee [5]: off-the-shelf hw, crowdsourcing

While Bayesian framework was used to present the belief of the robot pose and construct signal map in the previous works, LiFS [8] approximated the environment by a grid-based method. The grids are then transformed to *stress-free floor plan* where the grids were clustered based on walking-distance among each other rather than physical distance; due to the fact that in indoor settings not every neighboring grids are accessible from one to another within one step. The fingerprints are then collected during a walk in the localization environment, as the proposed data acquisition algorithm labels fingerprints with the number of steps taken. The signal map were then constructed with the observed fingerprints with a Multidimensional scaling technique [9]. After acquiring fingerprint space and stress-free floor plan, the correspondence between two information was then calculated to map one to another; thus, spatial information was tied to fingerprints of the AP's. This work achieved comparable localization results but depending on

ArrayTrack [10]: One of the best

Walkie-Markie [11]: spatial-pattern

SpotFi [12]: One of the best

B. Indoor Localization with Machine Learning

kNN: [13]

Neural networks: [14]

SVM: [15]

Deep-Fi [16]: Deep learning

In the scope of WiFi localization systems, it is still an open problem in the field of robotics to deal with this problem with off-the-shelf AP's, while resulting relatively higher localization results than other applications where NLoS observation can happen anytime.

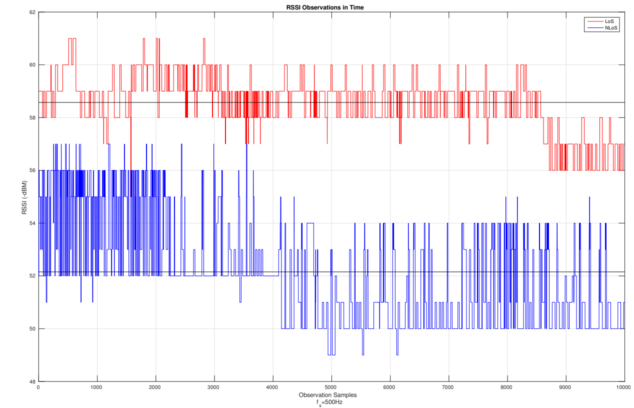

Fig. 1: RSSI readings of NLoS and LoS AP's acquired with a stationary agent

III. MFMS

A. Offline Stage

1) Data Acquisition:

2) Training:

B. Online Stage

1) Inference:

2) Information Fusion:

IV. Experimentation

A. Experimental Setup

1) Hardware: Fetch [17]

2) Software: ROS [18], Caffe [19]

B. Results

V. Conclusion and Future Work

ACKNOWLEDGMENT

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] H. T. Friis, "A note on a simple transmission formula," *Proceedings of the IRE*, vol. 34, no. 5, pp. 254–256, 1946.

[4] 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.

[5] 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.

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

[8] 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.

[9] I. Borg and P. J. Groenen, *Modern multidimensional scaling: Theory and applications*. Springer Science & Business Media, 2005.

[10] 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.

[11] 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.

[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] 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.

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

[15] 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.

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

[17] E. Ackerman, "Fetch robotics introduces fetch and freight: your warehouse is now automated," *IEEE Spectrum*, 2015.

[18] M. Quigley, K. Conley, B. Gerkey, J. Faust, T. Foote, J. Leibs, R. Wheeler, and A. Y. Ng, "Ros: an open-source robot operating system," in *ICRA workshop on open source software*, vol. 3, no. 3.2. Kobe, Japan, 2009, p. 5.

[19] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell, "Caffe: Convolutional architecture for fast feature embedding," *arXiv preprint arXiv:1408.5093*, 2014.