Title

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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, 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. 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

Indoor localization is an important problem in which an object of interest, i.e. a robot in our framework, suited with different sensors localizes itself in an indoor environment where there is no global positioning information is available. *The complexity of the problem significantly # exponentially increases as NLoS of reference AP's, presence of hard-constraints, in particular infrasractural elements such as walls and doors, noisy nature of the signals, and dynamic environments.* [3] *As robotic systems find more applications in indoor areas where dynamic objects, such as other robots and humans, often coexist, it increasingly becomes important to safely and accurately localize the agent.* Thus, a great amount of interest has been showed from both academia and industry. # *Do I really emphasize industry academia, actually this is a good opportunity to mention iBeacon from Apple* The indoor localization systems based WiFi signal can be mainly categorized undepngr two categories: fingerprinting and model-based methods [4]. We'll, however, only cover the fingerprinting technique due to the increasing popularity of the technique.

A. Indoor Localization Based on Fingerprinting

Fingerprinting-based systems are often had been surveyed many times [5] with different scopes. Zee [6]: 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 [7] is an examplary instance falling into the former category. The system aims for

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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 [8]: PF, dead reckoning

Zee [6]: 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 [9] 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 [10]. 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 [11]: One of the best

Walkie-Markie [12]: spatial-pattern

SpotFi [13]: One of the best

B. Indoor Localization with Machine Learning

kNN: [3]

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.

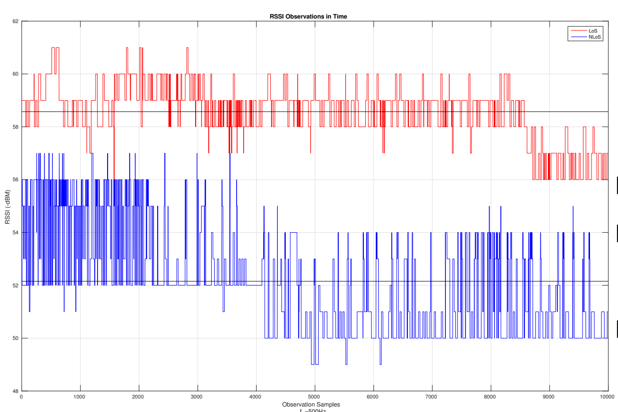

Fig. 1. RSSI readings of NLoS and LoS AP's acquired with a stationary agent

III. Problem Formulation

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: Fetch [17]

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

B. Results

VI. Conclusions

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Turkish Government and stuff

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