A Multifrequency Multistage Radiolocation System Based on Fingerprinting

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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

II. Fundamentals of Radio Wave Propagation and Radiolocationing

This section will cover the fundamentals of radiowave propagation and radiolocationing systems based on fingerprinting. First the radio wave propagation will be formulated and existing methods for radiolocation systems will be covered.

The fundamental 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 [1].

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

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 $d = 0$ and $d < \lambda$. Thus, received power generally denoted relative to a reference point d_0 with a prior corresponding received power.

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

Along with representing modeling the received power with a reference point, path loss is another common terminology used in field. The path loss is the difference between received and transmitted power in decibel scale as positive gain. Equation (4) represents path loss relative to a reference point. One of the major advantages of log-distance path loss model over Friis' free space model is that log-distance path loss model can account for different spaces by varying values of n.

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

where n is the path loss exponent and varies depending on the environment. Please note $n = 2$ for empty space. As it can be seen in the Equation (4), the received power and separation distance has a log-linear relationship. One example system proposed is EZ [2] which employs the log-distance model with a Genetic Algorithm based optimizer along with a Particle Filter (PF) fusing location estimates with inertial measurements.

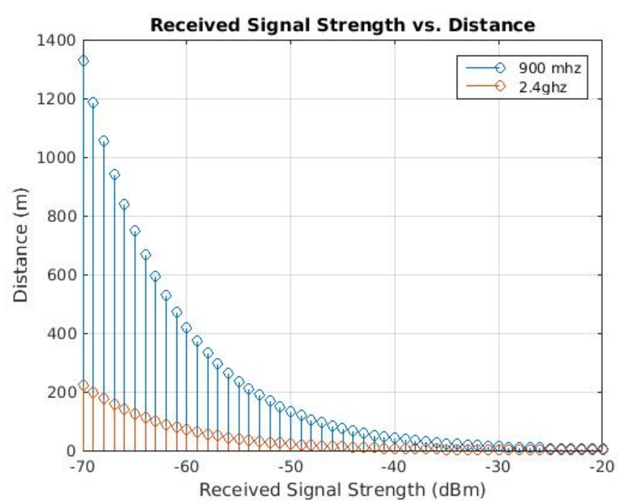

Fig. 1: RSSI readings of NLoS and LoS AP's acquired with a stationary agent

Figure 1 demonstrates the log-distance relationship between received power and the separation between two antennas in two different frequencies in Ultra High Frequency (UHF) radio band. This figure implies two fundamental problems in radiolocationing systems: The first problem is that as the carrier frequency increases path loss increases significantly, which limits the radio covarage and localization ability of the system in a large environments. On the other hand, as the carrier frequency increases, the separation between two antennas, i.e. the anchor node and the target to be localized, can be identified in finer resolution. Therefore, the trade-off between radio coverage and localization resolution can be resolved by employing different frequencies in indoor localization systems by fusing the information acquired from the anchor nodes.

A. Indoor Localization Based on Fingerprinting

This section of the paper will cover the existing fingerprinting-based indoor radiolocation systems. Fingerprinting-based radiolocation systems had been surveyed many times [3, 4] with different scopes due to its popularity in both academia and the industry.

Horus [5] is one of the early methods relying on Bayes' theorem and spatial clustering. While Horus achieves a significant improvement in localization accuracy, the computational complexity

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 anchor nodes. UnLoc [7] 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 anchor node in a specific region.

Particle filter [8]: PF, dead reckoning

Zee [6]: off-the-shelf hw, crowdsourcing RADAR [9]: One of the earliest While Bayesian framework was used to present the belief of the robot pose and construct signal map in the previous works, LiFS [10] 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 [11]. 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 [12]: One of the best

Walkie-Markie [13]: spatial-pattern

SpotFi [14]: One of the best

kNN: [15]

Neural networks: [16]

SVM: [17]

Deep-Fi [18]: Restricted Boltzman Machine (RBM)

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. 2: 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 [19]

2) Software: ROS [20], Caffe [21]

B. Results

V. Conclusion and Future Work

ACKNOWLEDGMENT

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