Indoor Distance Estimation using LSTMs over WLAN Network

Hitachi AI Conference, 2020

P. Sankhe, S. Azim, S. Goyal, T. Choudhary,
K. Appaiah, S. Srikant

Tuesday 28th July, 2020

Indoor Positioning System (IPS)

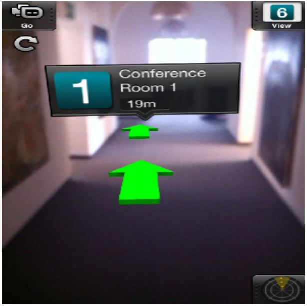
- Estimating the position/location of an object or device in an indoor environment setting (closed rooms, buildings, etc.)
- Similar to Global Positioning System (GPS)
- Instead of using satellites, IPS relies on nearby anchor nodes with known positions
- Anchors either actively locate the target object or provide environmental context

Problems with GPS in indoor environments

- Lack of strong GPS signal reception in indoor environments
- GPS indoor localization accuracy limited due to -
  - Signal attenuation and scattering by walls, roofs, and other obstacles
  - GPS satellites do not transmit strong enough to reach indoors
  - Signals that enter buildings are unreliable due to multiple reflections and thus give inaccurate distance measures

- GPS Localization error in indoor environments $\sim$ **4 - 10 m** (approx) and even more than that
- Insufficient for high accuracy demanding indoor positioning applications

Precise and rapid indoor location service enables



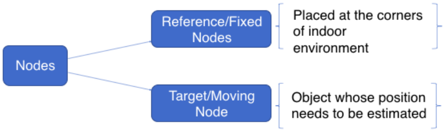
- Fine-grained precise location in complex indoor settings - supermarkets, libraries, museums, airport, warehouses, etc.
- Augmented reality support on the smartphone, wearables or glasses
- Asset Tracking

Existing IPS Methods

- Based on light, radio waves, wireless signals, vision, acoustic signals, etc.
- WiFi-based solution popular because WiFi is ubiquitous and densely deployed
- WiFi-based solution depends on acquiring various signal parameters -
  - **Received Signal Strength Indicator (RSSI)**: commercial standard WiFi chips
  - Channel State Information (CSI): available on some specific WiFi devices
- **Examples:** ArrayTrack (6-8 antennas), LTEye (rotatory antennas), Ubicarse (motion sensors, user involvement)

Proposed Approach: System Design

- Overall system
  - 3 Wireless Access Point (WAP)
  - single or multiple target nodes
  - N reference or fixed anchor nodes



- Function of reference nodes: To model the surrounding environment topology
- Number and configuration of reference nodes dependent on indoor topology

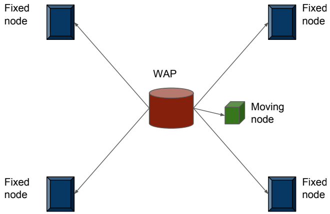


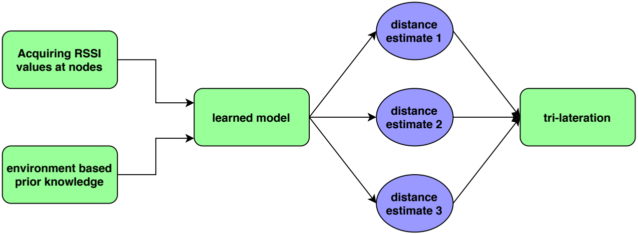
Figure: *System model: a WAP, 4 fixed reference nodes (known position) and a moving target node. Nodes are wirelessly connected to the WAP network*

Figure: *NodeMCU: configurable WiFi Module running on ESP8266*

Proposed Approach: Overview

- Acquiring RSSI values of the connection between the transmitter (WAP) and the receivers (the nodes)
- Using data-driven model to estimate the target node's distance from the WAP
- Exploit the dependence of RSS at any node on its distance from WAP and surrounding topology

$$d(target, WAP) = f_S(RSSI) \tag{1}$$



Proposed Approach: Trilateration

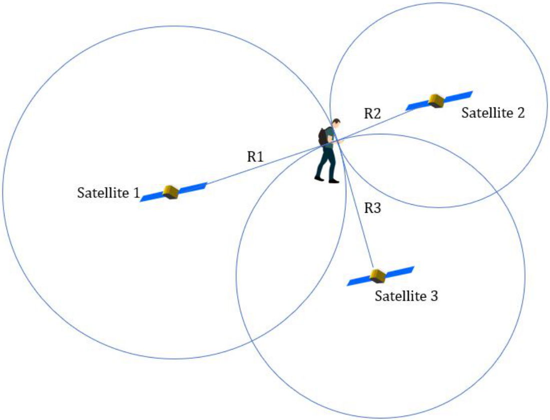
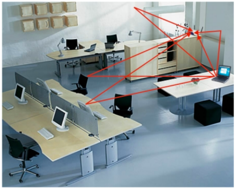
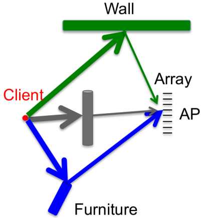


Figure: *Trilateration: estimating target device location using estimated distances from the three WAP*

Proposed Approach: Path Loss Effects

- Path-Loss happens during signal propagation from the transmitter to the receiver
  - *Shadowing*: Effect causing RSS to fluctuate due to obstruction of signal path
  - *Multipath*: Signal arriving at receiver via multiple paths causes temporal variations





- Path-loss effects vary spatially and temporally depending on surroundings changes
- LSTM based model employed to model the RSS correlation across time
- Reference nodes employed to take into account the surrounding spatial topology

Experimental Setup

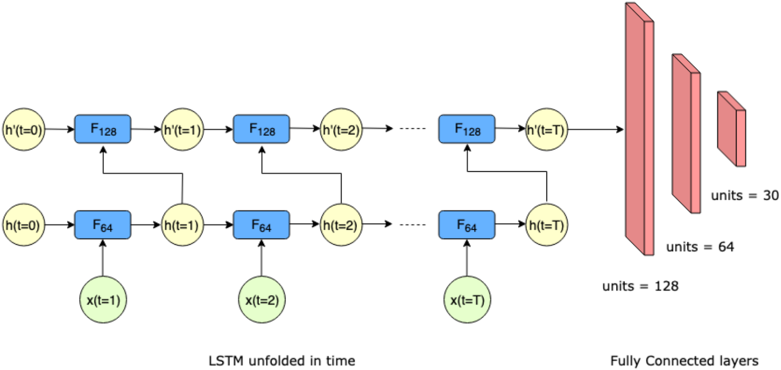
Data Collection

- Recorded RSSI data between nodes and the WAPs
- Ground-truth distance of the moving target node from the 3 WAPs collected using precise Vicon-based camera system

Problem Formulation

- Distance estimation problem formulated as classification task over equal-sized bins
- Model learns to predict the bin-class and reports the center of the predicted bin as estimated distance from WAP

Model Architecture



- 2 stacked LSTM layers followed by fully-connected layers
- F_n represents LSTM cell, $h(t)$, $h^{'}(t)$ & $x(t)$ represent cell states, input features resp.

Results & Comparisons

- Average localization error of 5.43 cm with correctness confidence of 93%
- System's adaptability validated by evaluating performance at multiple different indoor locations

Test location	5.43 cm Accuracy confidence (in %)	Average error upper bound (in cm)
location 1	93.94	8.67
location 2	92.51	7.36
location 3	93.89	8.12
location 4	92.99	8.55

Results & Comparisons

Methods	**Average Errors**	**Scale**
Ibrahim et al.	277 cm	A City Building
Lukito et al.	83% Classification Accuracy	University Campus
Wang et al.	94 cm	Room of dimension $\mathbf{4}$ m $\times$ $\mathbf{7}$ m
Sadowski et al.	48.6 cm	Room of dimension $\mathbf{10.8}$ m $\times$ $\mathbf{7.3}$ m
Our Method	8.67 cm	Room of dimension $\mathbf{8.46}$ m $\times$ $\mathbf{6.98}$ m

- No specific benchmark for comparing two different IPS system performance
- System performance depends on various factors -
  - hardware used
  - system setup requirement
  - position estimation algorithm
  - accuracy in various indoor settings

Thank You for your attention !!!