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Indoor Distance Estimation using LSTMs over WLAN Network

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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

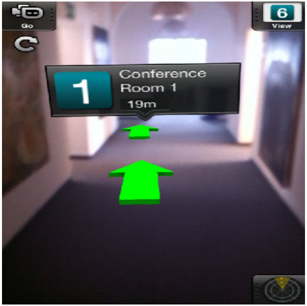
Problems with GPS in indoor environments

- 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

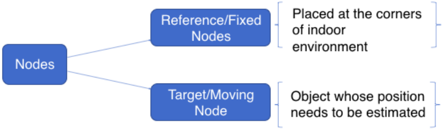


Existing IPS Methods

- 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

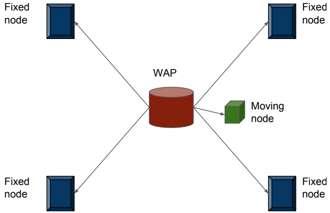


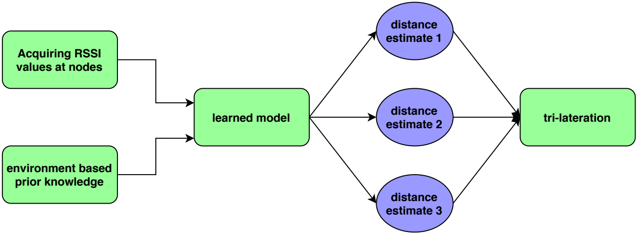
Figure: *System model: a WAP, 4 fixed reference nodes (known position) and a moving target node. Nodes are wirelessly connected to the WAP network*

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

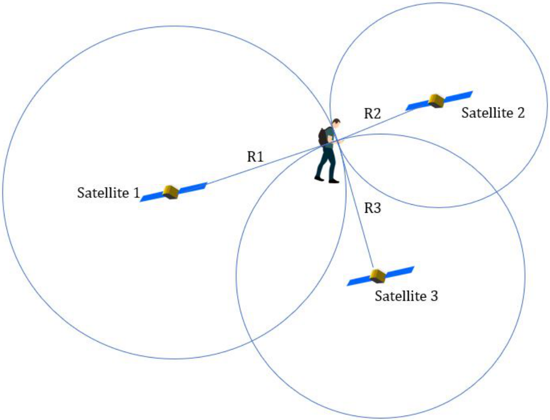
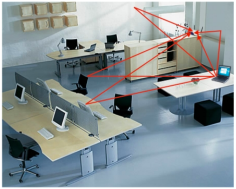
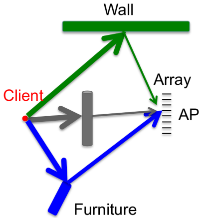


Figure: *Trilateration: estimating target device location using estimated distances from the three WAP*

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

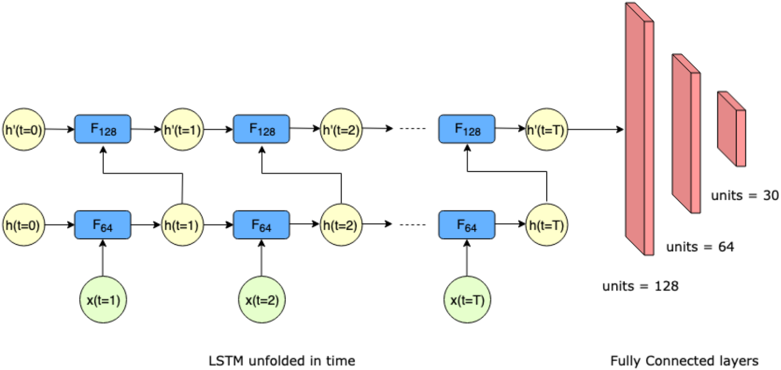
Data Collection

- 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 **4** m × **7** m
Sadowski et al.	48.6 cm	Room of dimension **10.8** m × **7.3** m
Our Method	8.67 cm	Room of dimension **8.46** m × **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 !!!