



Introduction to my bachelor thesis

RSSI & Magnetometer Based
Fingerprinting Localization In Indoor
Wireless Environments



Outline

- Basics
- The current localisation approach
- Main goals
- Preliminary results
- To-Do's

Basics

RSSI (Received signal strength indicator)

- Strength of wireless signal (dbm)
- Depends on
 - Distance
 - Environnement (walls)

➔ WiFi module 

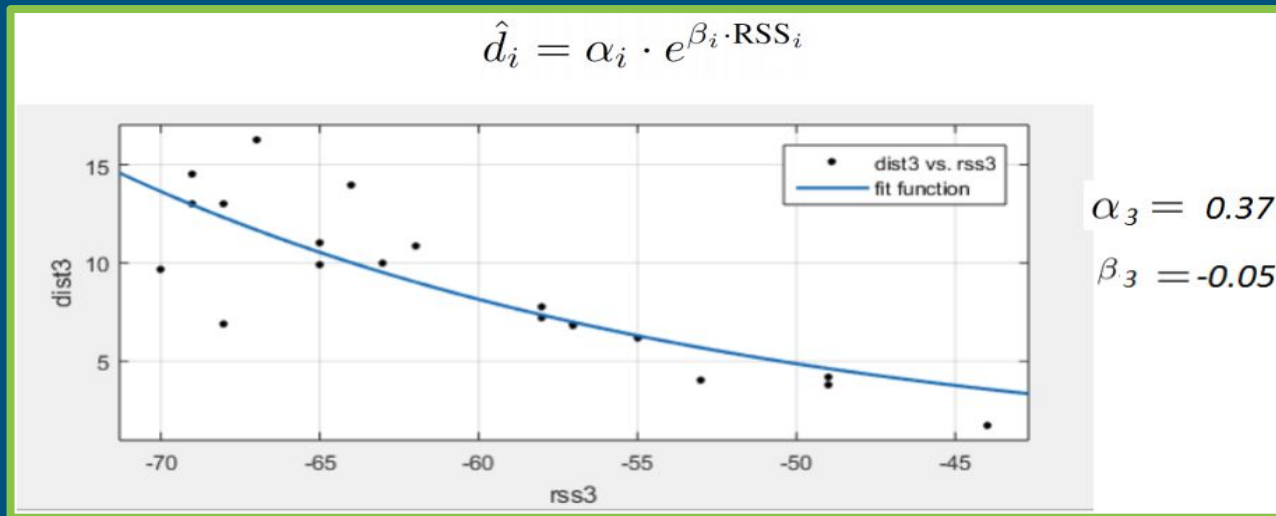
Magnetic field

- Earth's inherent magnetic field
- Outdoor case:
 - Mostly undisrupted
- Indoor case:
 - Disrupted by electronics and metal objects

➔ Magnetometer sensor 

The current localisation approach

Training



Production



RSSI

regression model

Distance
to AP

triangulation

Location

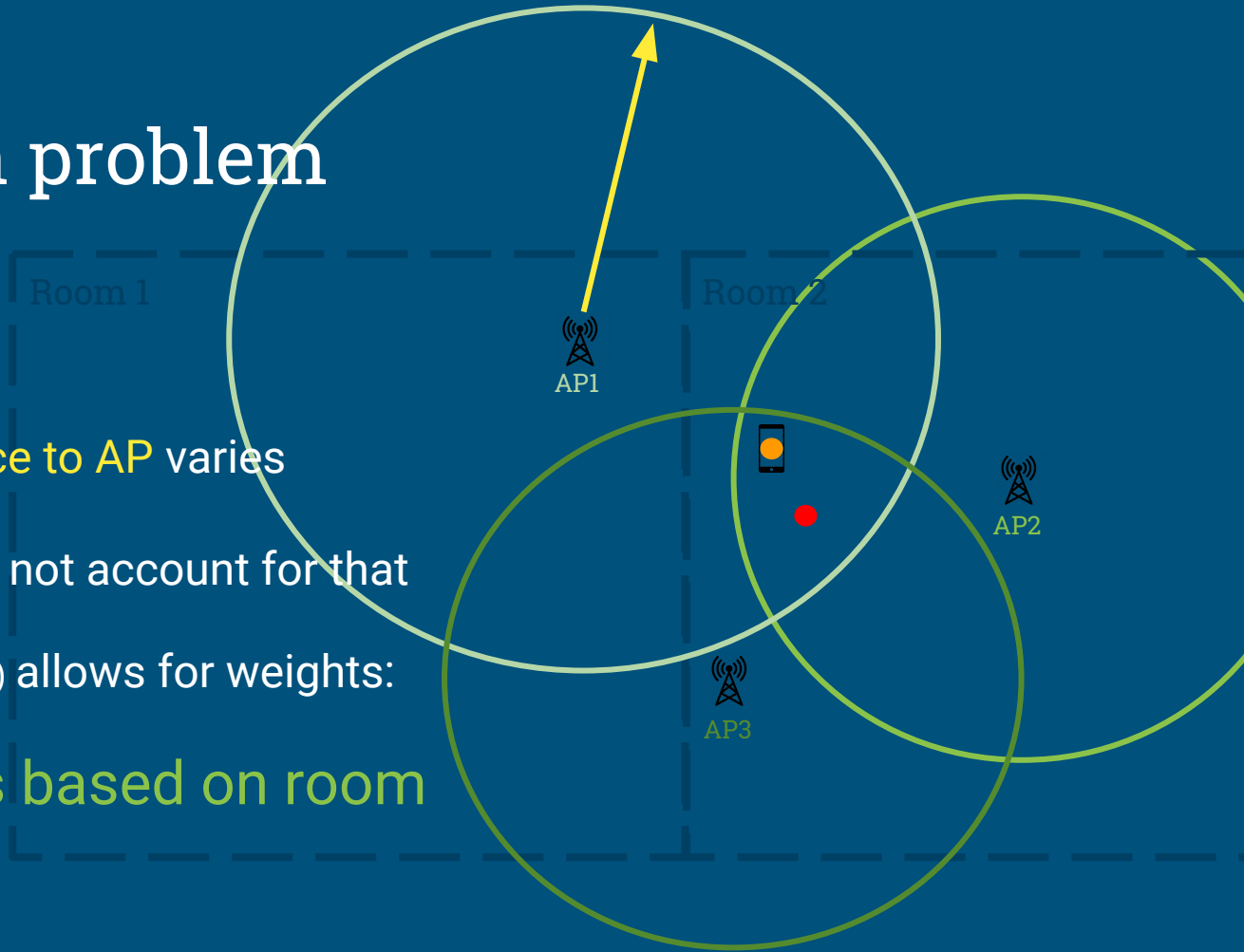
Triangulation problem

Problem

- Accuracy of **distance to AP** varies
 - due to walls etc.
- **LLS** algorithm does not account for that

WLS (weighted least squares) allows for weights:

➔ **Define weights based on room**



Main goals

- Room recognition
magnetic field & RSSI fingerprint
- Improve current localisation approach
Adjust triangulation weights based on room

Room recognition - fingerprinting

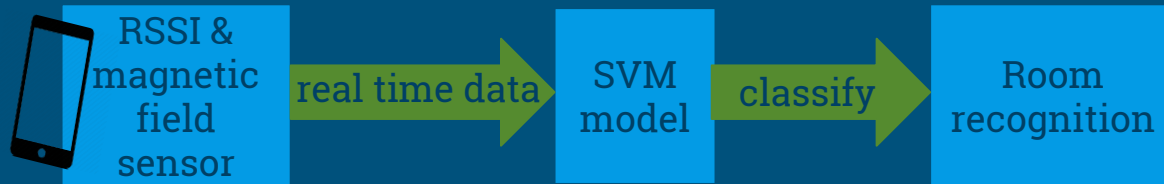
Assumption

- RSSI & magnetic field data can be used to recognize the room

Training Phase



Testing/production Phase



Improve localisation - define weights for WLS

Prerequisites

- Room recognition
- Regression model for **distance to AP**

Assumption

- Defining different weights for each room improves the accuracy of WLS

Question

- How do we determine the optimal weights?

Room recognition - methodology

Feasibility

Questions

- Does it work?
- What infrastructure is needed?
- What data is important?
 - Effect of magnetic field data
 - Density of measurements

Methodology

- Testbed: My Apartment
- AP's: my own & neighbours
- Gathering different datasets
- Comparing results of SVM classifier

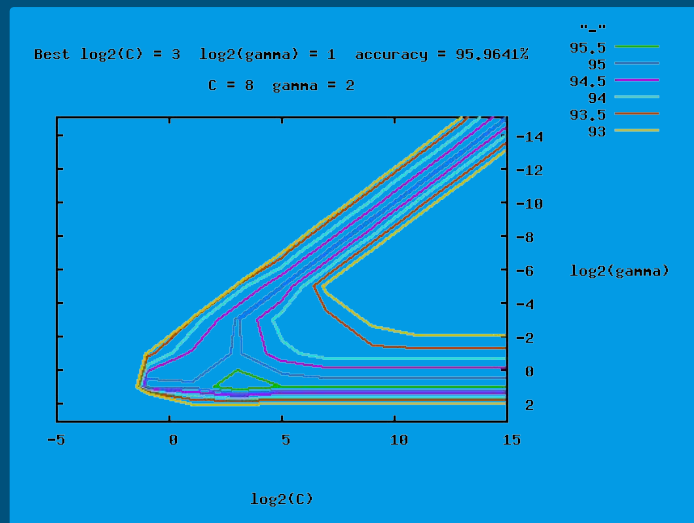
Room recognition - findings

Feasibility

- It works with high accuracy (89%)
- No special infrastructure needed
- Magnetic field data is important
 - 40% increase in accuracy
- Data-density affects accuracy

Best Results:

- Very high density at borders
- Low density in room center



4	TP-LINK_BCC3A8:-79	NETGEAR31:-69	Beatevents_WLAN:-59	devolo-000B3B9BC9A9:-58	UPC0048103:-56	489-652:-71	Berntiger:0	X-Axis:21	Y-Axis:-86	Z-Axis:-125
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2	TP-LINK_BCC3A8:-83	NETGEAR31:-74	Beatevents_WLAN:-67	devolo-000B3B9BC9A9:-66	UPC0048103:-62	489-652:-63	Berntiger:-74	X-Axis:38	Y-Axis:-99	Z-Axis:-122
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ToDo's

- Build a testbed at uni ✓ can use existing testbed
- Build fingerprint database for the testbed ✓
- Test the room recognition ✓ 91% accuracy in early tests
- (maybe) improve the room recognition → Neural Networks
- Regression model for **distance to AP**
- Define weights for each room
- Compare the accuracies of LLS and WLS

Q&A

Thank you for your attention