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Received signal strength-inertial sensor based fingerprinting localization in indoor wireless environments

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by Carl BALMER

Abstract

In this thesis a new indoor localization system is proposed, combining fingerprinting and range-based approaches. The main contributions are a room recognition system based on fingerprinting and a new weighting method for range-based trilateration using the information provided by the room recognition.

The system is implemented and evaluated in a test bed deployment on a floor of the university building. The results show that the room recognition is able to achieve high accuracy (80-90%) even with a small number of training samples. The room recognition based weighting method does increase the accuracy of the range-based localization. It does, however, not perform better than existing simpler weighting methods.

Acknowledgements

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List of Abbreviations

AN	**A**nchor **N**ode
MN	**M**obile **N**ode
CDS	**C**ommunication and **D**istributed **S**ystems
RSSI	**R**eceived **S**ignal **S**trength **I**ndicator
OLS	**O**rdinary **L**east **S**quares
WLS	**W**eighted **L**east **S**quares
LOS	**L**line **o**f **S**ight
NLOS	**N**on **L**line **o**f **S**ight
PDR	**P**edestrian **D**ead **R**reconing
SVM	**S**upport **V**ector **M**achine
RP	**R**eference **P**oint
TP	**T**est **P**oint
k-NN	**K**-**N**earest **N**eighbor
NLR	**N**on-**L**inear **R**egression
CDF	**C**umulative **D**istribution **F**unction
STD	**S**tandard **D**eviation

Chapter 1

Introduction

The main focus of this thesis is indoor localization of mobile devices especially smartphones.

With today's ubiquity of mobile computing, it has become evermore important for these devices to be aware of their location. Location awareness is fundamental for many possible applications such as pedestrian navigation and location based marketing in large building complexes (e.g. universities, airports, hospitals) or audio-guides for museums.

In contrast to outdoor localization, where we have GPS and other established solutions, indoor localization still remains challenging. Some of the reasons for this include the inability of the GPS signal to penetrate into the building and the effects of non-line-of-sight and multipath propagation on radio waves deteriorating the signal to be less accurate for localization[3, 14]. In addition to these challenges indoor location based applications usually require higher accuracy than those outdoors; An error of four meters is acceptable for street navigation but not for a museum guide.

1.1 Motivation

Indoor localization has been an active research field in the last few years with many different techniques proposed [13, 8]. One common approach is to base the localization on WiFi radio signals. WiFi infrastructure is already present in almost every building and can easily be upgraded with standardized off the shelf hardware. These radio-based techniques are usually classified into range-based and range-free methods[11].

Fingerprinting is a common range-free method, where known radio parameters are mapped to a location. Later this map is used to determine the devices location based on the current radio parameters. Fingerprinting can achieve good accuracy but creating the map is very labor intensive[11].

Range-based methods use the radio parameters to try to approximate the distance between the mobile device (Mobile Node) and the signal emitters (Anchor Nodes). This process is called ranging. Trilateration is then performed on these distances to determine the position of the MN. The ranging process is prone to errors caused by NLOS and multipath propagation.[11].

1.2 Overview and Contributions

In this work I propose a localization system which combines the range-based and fingerprinting approach, using fingerprinting to improve the range-based approach.

The range-based approach is extended by a room recognition system based on fingerprinting with WiFi and magnetic field data. The information provided by the room recognition is used to assign weights to the ranges based on the devices current room and so improve the trilateration and improve the accuracy of the range-based approach.

The proposed localization system is implemented in a test bed and the room recognition and weighting method are evaluated.

My main findings are summarized as follows:

- The proposed room recognition method is able to achieve very high accuracies even with only a small number of training samples.
- The inclusion of magnetic field data significantly improves the accuracy of the room recognition.
- Defining trilateration weights based on the room recognition increases the localization accuracy. The results are, however, not significantly better than existing simpler weighting methods.

1.3 Structure of this Work

In the remainder of this work, and the theoretical background is reviewed in chapter 2. The proposed localization system is introduced in chapter 3 and the room recognition and weighting are explained in detail. Chapters 4 and 5 deal with the test bed implementation used for the evaluation and the evaluation results respectively. Final chapter 6 summarizes the work and concludes the evaluation results.

Chapter 2

Theoretical Background

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Indoor localization has been a active research field in the last few years. In this chapter the two most common approaches, fingerprinting and range-based, are introduced and their components explained in detail. For the fingerprinting approach I will also talk about *support vector machines* and *the magnetic field in indoor environments*. Although they are not normally used in with fingerprinting they play a vital role in the room recognition system proposed in chapter 3. So understanding these concepts will be important.

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2.1 Range-Based Localization

A range based localization system consists of two main components.

A number of Anchor Nodes (ANs) which are placed at known locations and constantly transmit a radio signal.

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A mobile node (MN), in this case a smartphone, whose location is unknown and needs to be determined.

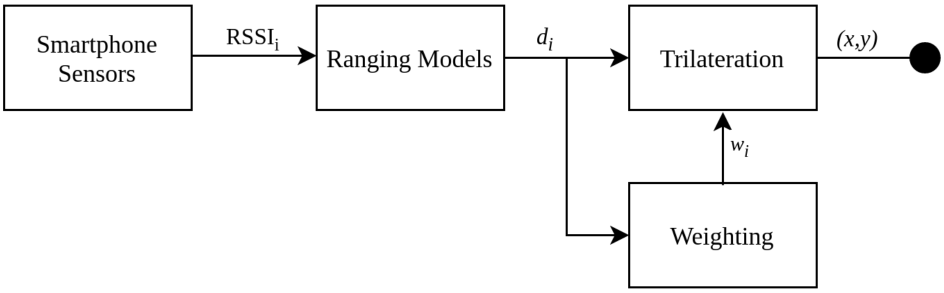

FIGURE 2.1: Block diagram of the range based localization approach.

To determine its position the mobile node measures the received signal strength from each of the anchor nodes $(RSSI_i)$. A ranging model is then used to estimate the distance (d_i) from the mobile node to each anchor node. Because the location of the anchor nodes is known, it is then possible to calculate the position of the mobile node using trilateration. To account for errors during the ranging step the trilateration can also be provided with a set of weights (w_i) representing the accuracy of each distance estimation.

The range-based approach to localization has the benefit of only requiring a few training samples to train the ranging models. It is therefore easy and not very labour intensive to implement. The problem is that in indoor environments the ranging models are often inaccurate, limiting the localization accuracy that can be achieved with this approach.

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In the following subsections the ranging, trilateration and weighting steps are described in further detail.

2.1.1 RSSI and signal propagation

The received signal strength indicator describes the total signal power received in milliwatts with the value expressed on a logarithmic scale (dBm)[15, p. 160]. In the case of Wi-Fi a value of -30 would mean a very strong signal while one of -90 would be so low as to be unusable (drowning in noise). In an open space without any obstacles the RSSI mainly depends on the propagation distance, but indoors several other factors become important. These are non line of sight (NLOS) and multipath propagation.

NLOS occurs when the signals path is obstructed by physical objects. The signal has to pass through these objects and therefore the RSSI is lower compared to LOS, where there are no obstacles[3].

Multypath propagation is caused when the signal is reflected from physical objects and arrives at the receiver multiple times with different signal strength. This causes inaccuracy and fluctuations in the measured RSSI as all these signals are blended together[14].

Both of these affects are very common in indoor environments, caused by the walls, people, furniture and other building materials. Furthermore the RSSI values are discrete and not fine grained what causes additional inaccuracy. This makes range-based localization based on RSSI challenging and limits its accuracy.

There are other ways to assess the signal strength, such as channel state information, which is more fine grained and can mitigate multipath effects, but they are not available on most mobile devices[3, 11].

2.1.2 Ranging

The ranging process estimates the distance between the ANs and the MN based on the radio parameters, in this case RSSI. This is done with non-linear regression (NLR) and the following model proposed by [12]:

$$d_i = \alpha_i e^{\beta_i RSSI_i} \tag{2.1}$$

It describes the loss of signal strength over the propagation distance. d_i is the estimated distance from the MN to the i-th AN, $RSSI_i$ is the i-th AN's signal strength as measured by the MN and α_i, β_i are environment variables specific to each AN.

The model needs to be trained for each AN individually by determining the values for α_i and β_i. This is done by fitting the function to a small set of training samples. This can be done using, for example, least squares optimization.

2.1.3 Trilateration

Trilateration is the process of determining a absolute or relative location based on the distance to known locations. In contrast to triangulation it relies on distances instead of angles.

In the context of localization the goal is to determine the NM's location (x, y) based on the the locations of the ANs $(\tilde{x_i}, \tilde{y_i})$ and the distance estimations d_i obtained from the path loss model.

The actual distance D_i from the MN to the i-th AN can be expressed as follows:

$$D_i = \sqrt{(\tilde{x_i} - x)^2 + (\tilde{y_i} - y)^2} \tag{2.2}$$

Under the assumption that $d_i = D_i$ this leads to the following equation system:

$$\begin{pmatrix} d_1 \\ d_2 \\ \vdots \\ d_n \end{pmatrix} = \begin{pmatrix} \sqrt{(\tilde{x_1} - x)^2 + (\tilde{y_1} - y)^2} \\ \sqrt{(\tilde{x_2} - x)^2 + (\tilde{y_2} - y)^2} \\ \vdots \\ \sqrt{(\tilde{x_n} - x)^2 + (\tilde{y_n} - y)^2} \end{pmatrix} \tag{2.3}$$

But d_i is only an estimation so there is no exact solution of the above system. The best solution is the one that minimizes the sum of the squared error $d_i - D_i$. So to determine the MN's location the following problem has to be solved:

$$argmin_{x,y} \sum_{i=1}^{n} w_i \left(d_i - \sqrt{(\tilde{x_i} - x)^2 + (\tilde{y_i} - y)^2} \right)^2 \tag{2.4}$$

This can be done using a optimization algorithm like "Levenberg–Marquardt" or "Gauss-Newton".

2.1.4 Weighting

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The optimization problem in equation 2.4 also defines a set of weights w_i coresponding to each distance estimation d_i. In the context of trilateration these weights represent how accurate each distance estimation is.

The ranging models accuracy can vary greatly. By applying a large weight to the more accurate estimations and a small weight to the inaccurate ones it should, in theory, be possible to correct for the ranging error and improve the localization.

In practice the problem is, that the ranging error is not known. A weighting method is needed that estimates the ranging error.

Previous work at the CDS group [11] used the assumption that the ranging error is larger with increasing distance to the anchor node. So the weights were defined as inversely proportional to the estimated distances:

$$w_i = \frac{{d_i}^{-1}}{\sum_{n=1}^{N} {d_n}^{-1}} \tag{2.5}$$

In the remainder of this work this weighting method will be referred to as *Distance Weights*.

ok

2.2 Fingerprinting

Fingerprinting is a common method for localization based on RSSI[5]. It consists of two main phases.

In the offline/training phase a map of reference points (RP) is created by collecting RSSI values for each AN from known locations. Then in the ok online phase RSSI values are collected from an unknown location, called the test point (TP). The location of the TP is determined based on the RP-map using machine learning algorithms like a k-nearest neighbor regression[3].

The accuracy of this method mainly depends on the density of the RP-map. The higher the density of RPs the better the accuracy. Generally achieving a satisfying level of accuracy, requires a lot of RPs. Other factors are the number of attributes in each RP and the variability of the observation parameters. ok

More attributes per RP, an attribute being a data value like a RSSI or a magnetic field measurement, gives the algorithm more information to work with and so increased the accuracy[10]. This effect is subject to diminishing returns[2]. A high variability in the observation parameters depending on location is also beneficial.

This approach is able to achieve good accuracies in an indoor environ- ok ment. The problem is that it is very labour intensive to create the necessary fingerprinting maps.

2.2.1 Magnetic field in indoor environments ok

Earths natural magnetic field has already been used for localization, mainly as a compass to determine the devices heading in PDR systems. However, ok the presence of magnetic field anomalies make accurate heading determination difficult for indoor applications. The anomalies are caused by the ferrous structures in the building materials, electrical devices, cables and tubes. Previous research suggests that these anomalies can be used in a fingerprinting approach to determine a devices location[9, 1, 10]. They show that the magnetic field anomalies have sufficient local variability and are mostly stable over time. Therefore they should be applicable for use in localization.

2.2.2 Support Vector Machine

The Support Vector Machine (SVM) is one of the most widely used machine learning algorithms. It predicts the labels of new (unknown) samples based on previous (known) examples. In its basic form it only supports two labels. This is called binary classification.

The known examples are called training data. It consists of instance-label pairs $(x_i, y_i)\,, i = 1, ..., l$ where $x_i \in R^n$ and $y_i \in \{-1, 1\}$. x_i represents the samples's observable features while the label y_i defines in which category it belongs.

The SVM maps the samples into n-dimentional space and then tries to fit a hyperplane through that space separating the two classes so that ideally ok all samples with $y_i = 1$ are on one side of the hyperplane and $y_i = -1$ on the other. To make the separation as clear as possible the margin between the hyperplane and the samples is maximized at the same time. The samples which lie directly on the margins are called the support vectors.

To classify a new unknown sample the SVM determines on which side of the hyperplane it lies and assigns the according label.

To fit the hyperpalane the SVM solves the following optimization problem[4]:

$$\begin{aligned} \min_{\omega,b,\xi} \quad & \frac{1}{2}\omega^T\omega + C\sum_{i=1}^{l}\xi_i \\ \text{subject to} \quad & y_i\left(\omega^T\phi\left(x_i\right)+b\right) \geq 1-\xi_i, \\ & \xi_i \geq 0, i=1,...,l \end{aligned} \tag{2.6}$$

There may be outlines in the data, so a hyperplane that separates all samples correctly may not be the best classifier. To account for this, a cost is paid if a sample violates the error term $y_i\left(w^T\phi\left(x_i\right)+b\right) \geq 1$, increasing the objective function by $C\xi_i$. The C parameter defines the trade-off between the simplicity of the decision surface (*hyperplane*) and misclassification of training samples. For large values of C the optimization will chose a hyperplane with a smaller margin, more support vectors and therefore more complex decision surface, trying to classify all samples correctly. Conversely, a small value of C will cause the optimizer to look for a larger-margin separating hyperplane, even if that hyperplane misclassifies some samples[6].

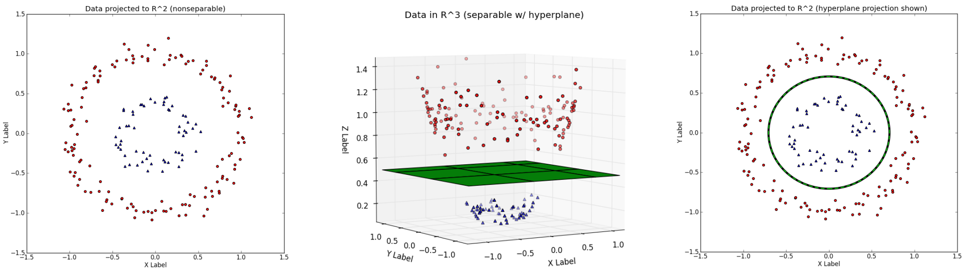

FIGURE 2.2: (Left) A dataset in, not linearly separable. (Middle)The same dataset transformed with decision boundary. (Right) The nonlinear decision boundary.

But the training data may not be linearly separable. In this case the so called kernel trick can be used. The kernel is a function $k\left(x_i,x_j\right)=\phi\left(x_i\right)\cdot\phi\left(x_j\right)$ which maps the features x_i to a higher dimensional space where they can be separated by a hyperplane. This results in a non linear separation in the original feature space[7].

To perform multi-class classification the "one-against-one" approach can be used. For k classes $k\left(k-1\right)/2$ classifiers are trained. Each binary classifier is then considered to vote for a class. The sample is then placed in the class with the most votes[4].

Chapter 3

The localization system

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In chapter 2 the two most common indoor localization approachers were introduced. In this chapter a localization system is proposed that combines those approaches, using fingerprinting to improve the range-based approach.

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The proposed system adds a room recognition system and new weighting method to the standard range-based approach (see chapter 2.1). The room recognition uses fingerprinting with $RSSI$ and magnetic field data to determine the devices current room. The new weighting method then relies on the information provided by the room recognition to more accurately estimate the ranging error and improve the trilateration accuracy.

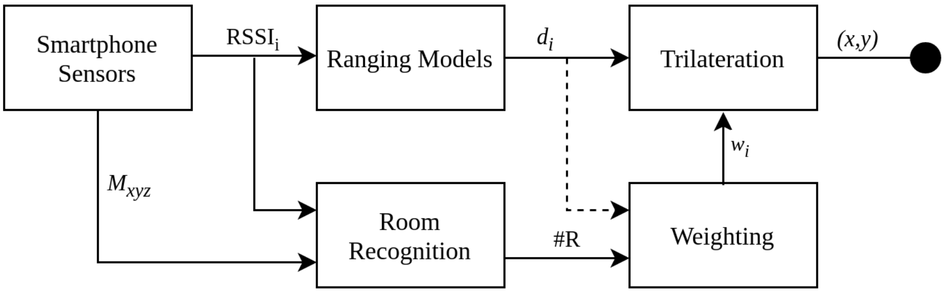

FIGURE 3.1: Block diagram of the proposed localization system.

As apparent in the block diagram (Figure 3.1) the standard range-based approach is not changed but simply extended. Therefore the main focus of this thesis are the two added components; the proposed room recognition system and weighting method. In the remainder of this chapter those components are explained in detail.

3.0.3 Room Recognition

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The room recognition system is based on a fingerprinting approach. The fingerprint-map consists of $RSSI$ and magnetic field data (B_{xyz}). A multi-class SVM classifier is trained with the fingerprinting map and can then be employed to predict the devices room.

Wile fingerprinting can be labour intensive when used for accurate localization, applying it to the problem of room recognition solves some of this problem. In this case it is not required to measure the exact location of each sample. The samples only need to be labelled with the room. This makes the sample collection a lot faster.

Magnetic field data (B_{xyz}) is also included in the fingerprinting map. It is predicted that this will increase the accuracy of the room recognition system as previous work has shown the applicability of magnetic field data for localization. *This hypothesis needs to be confirmed in the evaluation.*

Another question to be answered is what kind of fingerprinting map yields the highest accuracy; *a equally distributed map or a unequally distributed one with more samples at the borders* (walls and doors between rooms).

The support vector machine was chosen as the classifier because it is, compared to other common classifiers like k-NN , better suited for this kind of problem. It has no problems with outliers in the training data; It only chooses the most significant samples as support vectors. Also it performs well with a small amount of samples. k-NN on the other hand is very susceptible to outliers and generally needs more samples to offer good results.

3.0.4 Weighting

Supposed that the ranging error is mainly caused by obstructions to the signal (walls, wires etc.). This would mean that for any two samples inside one room the ranging error should be roughly the same. Therefore it should be possible to estimate the ranging error of a unknown sample by calculating the average error of some known training samples located in the same room.

The proposed weighting method defines the weights for each room as inversely proportional to the average ranging error for each anchor node. This results is a separate set of weights for each room. The room recognition is used to decide which set of weights to use.

For room R the weight w_{Ri} associated with the distance estimation d_i to anchor node AN_i is calculated based on all the training samples S_R in the room.

$$\begin{aligned} w_{Ri} &= \frac{E_i^{-1}}{\sum_{n=1}^{N} E_n^{-1}} \\ E_i &= \sum_{s=1}^{S_R} (D_{si} - d_{si})^2 \end{aligned} \tag{3.1}$$

The inverse ranging error for anchor node AN_i is divided by the sum of the inverse ranging error for all anchor nodes N. The ranging error is represented by the sum of the squared difference between the actual and estimated distance $(D_{si} - d_{si})^2$ for each training sample s $(s = 1..S)$.

In the remainder of this work this weighting method will be referred to as *Room Weights*.

I could also be beneficial to combine the new *Room Weights* with the *Distance Weights* from equation 2.5 by adding them together.

The effectiveness of both the *Room Weights* and *Room+Distance Weights* will need to be evaluated.

Chapter 4

Localization System Implementation

In order to develop and evaluate the system outlined in Chapter 3, it is first required to establish a testing environment. This chapter introduces the implementation of the localization system in a test bed.

4.1 System Overview

The test bed consists of multiple anchor nodes, a mobile node and a computer.

The ANs are commercial WiFi access pints, which are placed in the area of interest and constantly broadcast a beacon signal.

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The MN, an android smartphone, is used to collect samples form different location in the area of interest.

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The collected samples are transferred to the computer where the calculations and algorithms for training, testing and evaluating the system can be executed.

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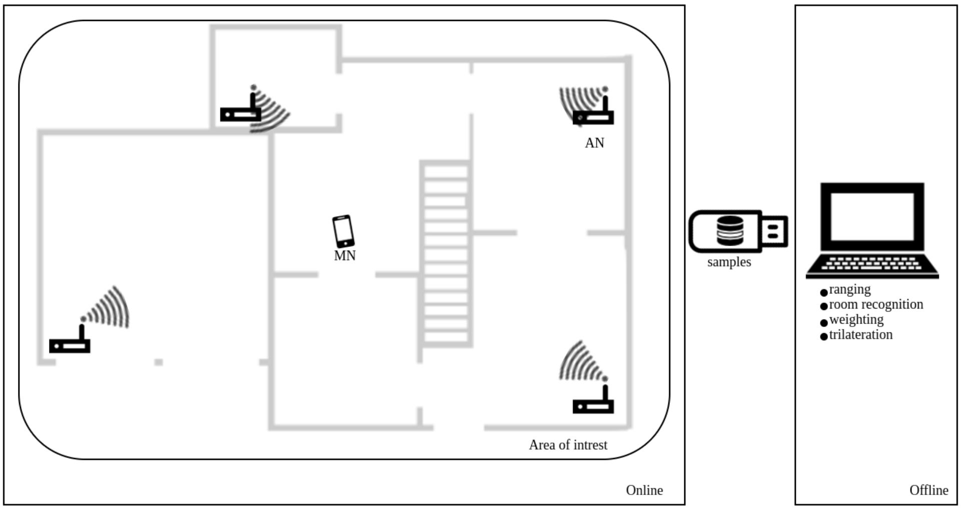

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FIGURE 4.1: Overview of the test bed implementation

This test bed implementation splits the system into an online (collecting samples) and offline (calculations on the computer) part. This way it is possible to try out and empirically compare different configurations of the localisation system under the exact same conditions.

The set-up of this test bed comprises both hardware and software specific configurations for each component. The remainder of this chapter details these configurations.

4.2 Hardware Set-up

This set-up requires three different kinds of machines. One for the AN, another for the MN and a computer. There are no special requirements for the computer as long as it is able to execute Java code.

For the AN and MN the following hardware was employed:

Anchor Nodes The commercial Wi-Fi access points used as anchor nodes are of the model D-Link D-635 and D-2553. They are set-up with a beacon period of 100ms and broadcast on the 2.4 GHz frequency band.

Mobile Node The mobile node is an android smartphone of the model *One Plus One*. It has the following specifications:

- **OS:** Android 5.1
- **Processor:** 2.5GHz Quad-core CPU
- **WiFi module:** Qualcomm WCN3680 802.11ac/FM/BT 4.0 Combo Chip
- **Internal sensors:** accelerometer, magnetometer, gyroscope, proximity, ambient light
- **Memory:** 3 GB RAM

The WiFi module and the magnetometer are used for the sample collection. The magnetometer is reasonably accurate while the off-the-shelf WiFi interface is prone to interferences.

4.3 Software Set-up

4.3.1 Sample collection

The samples are collected on the smartphone using a small application written for this purpose.

The samples consist of:

- **A label** eather indicating the room or the exact location where the sample was taken.
- **A set of RSSI values**, one for each AN.
- **The magnetic field strength** in μ-Tesla along the devices x,y and z axis.

On android the WiFi module can not be accessed directly. Wi-Fi scans have to be initiated through the `AndroidAPI` and it only supports full scans[2]. Full scans take longer so it is only possible to take one RSSI measurement every 1.5 seconds.

Due to the low sampling rate it is not practical to apply filters to remove noise from the $RSSI$. It is also not possible to access channel state information which could be used to mitigate some of the multipath effects.

To collect one sample the application takes the average of five RSSI and magnetometer measurements, each spaced 2 seconds apart. The samples are then saved to a `.csv` file on the smartphones internal storage and later transferred to the computer.

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4.3.2 Training and testing of the system

Training, testing and evaluation of the localization system is done offline on a computer using Matlab, WEKA and a Java program for the trilateration.

First the collected samples are grouped into training and testing datasets and the ranging, room recognition and weighting models are generated from the training data.

Then the trilateration-tool reads the testing data, applies the models and solves the trilateration problem. It prints out the predicted position and the positioning error for each sample in the testing set.

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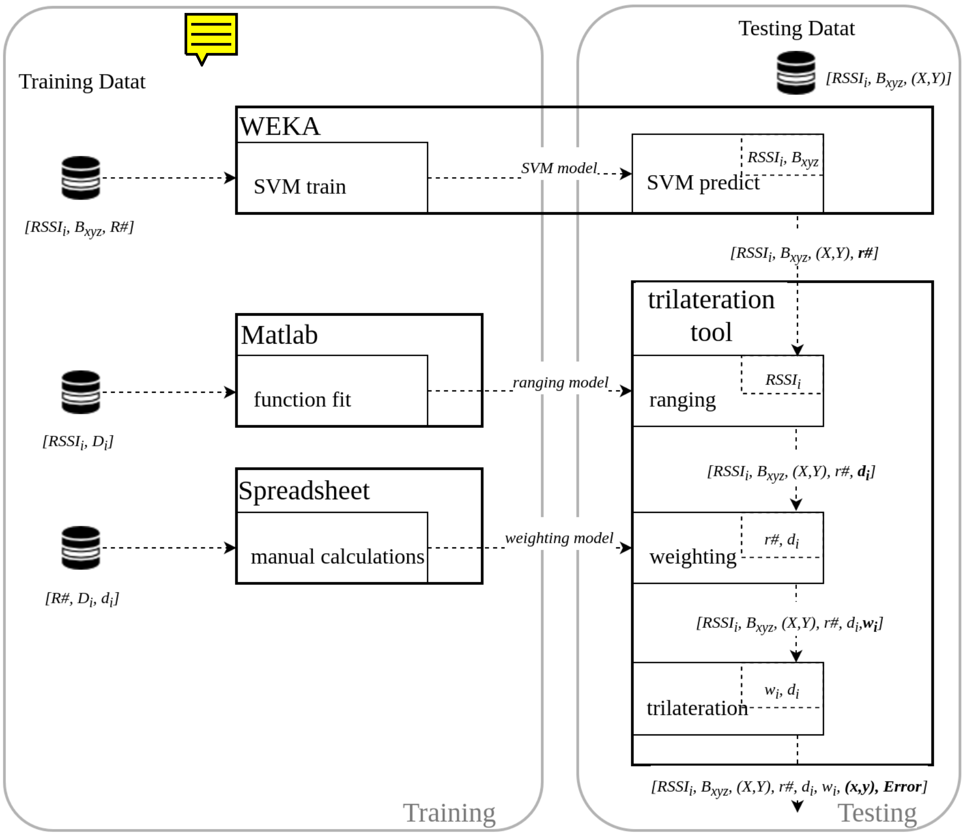

FIGURE 4.2: Diagram of the offline implementation

Room Recognition Model

The SVM for the room recognition is trained in WEKA. It generates a multiclass SVM model from the training data set and may use grid search for the parameter selection. The training data set consists of samples containing RSSI $(RSSI_i)$ and magnetic field (B_{xyz}) values labelled with the room number $(R\#)$.

Ranging Model

For the ranging model the α, β parameters from equation 2.1 need to be determined for each AN. This is done by fitting the equation to the testing data in *Matlab*. The testing data set is a list of RSSI values and the corresponding distance (D_i) to the AN.

The resulting non-linear regression model is inaccurate with high RSSI values (samples verry close to the AN). To account for that the distances for these high values are set by hand.

Weighting Model

The *Room Weights* are calculated by hand based on equation 3.1 in a spreadsheet program and imported into the trilateration tool.

The *Distance Weights* are calculated by the trilateration tool during run time based on the equation 2.5.

Testing

The testing dataset contains samples with RSSI and magnetic field values and the position (X, Y) where the sample was collected.

In a first step WEKA is used to predict the room number. The result is handed to the trilateration tool, which applies the ranging and weighting models to determine the predicted distances (d_i) and clculate the weights (w_i). It then solves the trilateration problem (equation 2.4) using the Levenberg–Marquardt optimizer from the `Apache Commons Math` library. It outputs the predicted position (x, y) and the localization error to a `.csv` file.

Chapter 5

Evaluation

in the previous chapter 4 the test bed implementation was introduced. In this chapter this test bed is used to evaluate the performance of the system proposed in chapter 3.

The evaluated components of the system are the room recognition and the room based weighting method for the trilateration.

Before presenting the evaluation results section 5.1 introduces the environment where the test bed was deployed and the data sets used for the evaluation. Sections 5.2 and 5.3 then evaluate the room recognition and weighting method.

5.1 Test bed deployment and collected data sets

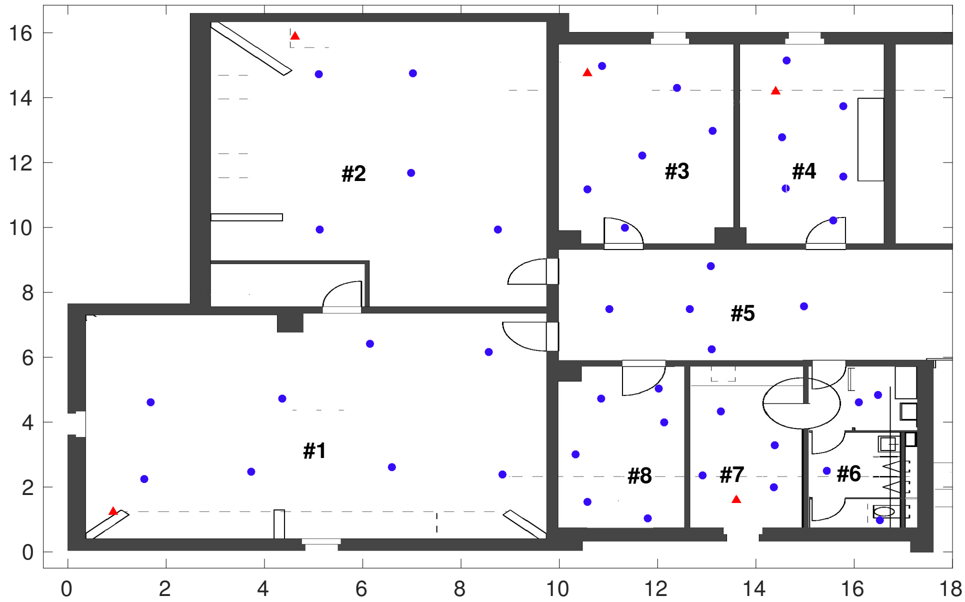

FIGURE 5.1: Floor plan showing the area of interest with the anchor nodes in red, the XY-samples in blue and the room numbers in black

The test bed was deployed on the third floor at the Institute of Computer Science (INF) of the University of Bern. The area of interest is 297m^2 in size, with seven rooms connected by a large corridor. The five anchor nodes were positioned to provide maximum coverage of the area so that the mobile node is able to receive at least four of the signals at all time.

The rooms were given numbers form one to eight, the corridor being also treated as a room.

5.1.1 Collected Data Sets

The samples were collected with the smartphone held approximatively one meter above the ground and always pointing in the same cardinal direction. This is important because the magnetic field measurements are influenced by the devices orientation.

The collected samples were grouped into the following data sets:

- **Fingerprinting data** only labelled with the room number
  - Grid (223 samples)

    A set of **evenly distributed** samples gathered in a grid pattern with approximately 1.2m distance between them.
  - Borders (373 samples)

    A set of **unevenly distributed** samples. The sample density is very high at the borders (walls and doors between rooms) with about one sample taken every 0.5m but only a few samples from the center of each room.
- **XY data** labelled with the exact coordinates

  A set of 44 **evenly distributed** samples labelled with (X, Y)-coordinates.

5.2 Room Recognition

The purpose of this evaluation is to check the hypothesis that the magnetic field data improves the room recognition accuracy and find out which kind of training data (evenly distributed or more samples at the borders) achieves the best results.

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To check if the magnetic field data has a significant impact on the performance of the room recognition 10-fold cross validation is performed on the evenly distributed *Grid* data set both with and without using magnetic field data. The resulting accuracies are compared. This experiment is repeated with different SVM parameters to see if the parameters have an impact on the result.

To determine the best training data set multiple models are generated using the two training data sets (*Grid*, *Borders*) and different SVM parameters and kernels. The models are tested against the evenly distributed *XY* data set and the resulting accuracies are compared.

The SVM parameters are either the standard pre-sets or selected with cross validation and grid search.

Evaluation Type	with B_{xyz}	without B_{xyz}	Difference
CV (pre-set)	90.1%	70.4%	19.7%
CV (optimized)	93.3%	83.0%	10.3%
Train: *Grid*, Test: *XY*	84.1%	81.8%	2.3%
Train: *Grid*, Test: *XY* *(without room #3)*	97.3%	86.8%	10.5%

ok

TABLE 5.1: Accuracy of the room recognition with and without magnetic field data.

Room Number	with B_{xyz}	without B_{xyz}	Difference
#1	100.00%	100.00%	-
#2	100.00%	100.00%	-
#3	0.00%	50.00%	-50.00%
#4	100.00%	83.30%	16.70%
#5	100.00%	80.00%	20.00%
#6	100.00%	75.00%	25.00%
#7	100.00%	100.00%	-
#8	83.30%	66.70%	16.60%

TABLE 5.2: Accuracy of the room recognition for each room (*XY* test set)

5.2.1 Results

Table 5.1 shows a large difference between the performance with and without magnetic field data when using cross validation. With WEKA's pre-set SVM parameters (poly-kernel, $c = 1, e = 1$) the improvement is very large with almost 20%. When using the optimal parameters (determined by grid search for each case separately) the difference drops to a still significant 10%. This drop is due to the fact that the pre-set parameters seem to be better suited to the case with magnetic field data. A comparison between the two cases using not optimal parameters is therefore unfair.

Cross validation can sometimes be a little biased. So the impact of magnetic field data was also compared by training with the *Grid* data set and testing against the *XY* data set, mincing a real-world use case of the room recognition. Surprisingly this only resulted in a 2.3% improvement.

The reason for this unexpected result can be found by comparing the impact of the magnetic field data on the room recognition accuracy for each room. We see in table 5.2 that the accuracy is improved in every room that was not already 100%. Wit the exception of room #3 where the accuracy drops to 0%.

At the time the data sets were collected room #3 was almost empty while the two adjacent rooms contained server racks and technical equipment (near the walls separating the rooms). I expect that some of this equipment caused a disruption of the magnetic field during the time that the *XY* data set was created. And therefore obscured the already weak magnetic signature of room #3. A similar effect was observed in related work [10].

When room #3 is excluded from the test set we get the expected 10% improvement when using magnetic field data.

Training Data **(#Samples)**	**Polynomial** $c = 1, e = 1$	**RBF** $c = 1, g = 0.01$
Grid (223)	81.8%	18.2%
Borders (373)	84.1%	11.4%

TABLE 5.3: Accuracy of the room recognition with different training data sets using the polynomial and RBF kernel presets

Training Data	**Polynomial**			**RBF**		
(#Samples)	**accy**	c	e	**accy**	c	g
Grid (223)	84.1%	10	1	84.1%	100	0.01
Borders (373)	88.6%	100	1	86.4%	1000	0.01

TABLE 5.4: Accuracy of the room recognition with different training data sets using the optimal parameters

Table 5.3 shows the accuracy for the two training data sets and two different kernel functions using WEKA's pre-set parameters. The polynomial kernel performs very well while with the RBF kernel the accuracy is below 20% for all training data sets. The RBF kernel, with these parameters, does not seem to be a good fit for this kind of data.

With the polynomial kernel the unequally distributed *Borders* data performs better. But it is only 2.3% better than *Grid*, which has 40% fewer samples. This difference does not seem significant and is most likely due to the higher numbers of samples.

Table 5.4 shows the accuracy with optimal parameters for each training set and kernel. The parameters were selected with a grid search.

For both training data sets the accuracy could be slightly increased by the parameter selection, but the relative accuracy is still the same; *Borders* has the highest performance with *Grid* only being marginally worse.

With the optimized parameters both kernels have a similar performance, although the RBF kernels c values are generally higher. A high c value means that the RBF kernel's decision surface needs to be more complex to achieve the same accuracy as the polynomial kernel. It is therefore not as good at separating the samples.

Finally to see if it is possible to train a room recognition system with a minimal number of samples the system was trained with the *XY* data set and tested against the *Grid*. This resulted in a accuracy of 81.2%. This is still very high considering only 44 training samples were used.

5.3 Weighting

Section 5.2 has shown that the proposed room recognition can achieve high accuracy even with a small training data set. Potentially it could be trained with the same points used to train the ranging model, eliminating the need to collect additional samples. It is now possible to evaluate the proposed weighting method and see if the information from the room recognition can be used to improve the range based localization accuracy.

In Chapter **??** a new weighting method was proposed; the *Room Weights* (equation 3.1). The goal of this evaluation is to evaluate if the *Room Weights* improve the accuracy of the trilateration and if this is true whether the accuracy can be further improved by combining the *Room Weights* with the existing method of the *Distance Weights*.

In a first step the new weighing method is applied with the assumption of 100% room recognition and compared to *ordinary least squares* (trilateration with no weights). This gives us a best case value for the improvements with the new weighting method.

In a second step the weighting method is applied to a real word scenario using a room recognition system trained with the the *Grid* data set (accuracy of 84%). The results are compared to the 100% case to see how sensitive the weighing method is to errors in the room recognition.

Finally the performance of the proposed weighting method under real world conditions is compared to the *Distance Weights* to see if it performs better than other simpler weighting methods.

The *ranging model* and *room weights* are trained with the entire *XY* data set and imported into the trilateration tool. For evaluation the same data-set is used.

5.3.1 Results

In addition to the mean, standard deviation and maximum error, the results are presented as the cumulative distribution function of the localization error. This allows for a more accurate representation of the performance than just using statistical values.

Weighting Method	**Mean**	**STD**	**Max Error**	**Improv over OLS**
OLS	2.74m	1.57m	8.25m	
Room Weights (100%)	2.35m	1.22m	4.89m	14.2%
Room+Distance Weights (100%)	2.29m	1.16m	4.65m	16.4%
Room+Distance Weights (84.1%)	2.40m	1.25m	5.69m	12.4%
Distance Weights	2.42m	1.19m	5.37m	11.3%

TABLE 5.5: Comparison of the statistical values for the different weighting methods

The results with 100% room recognition show a improvement of the *Room Weights* over *OLS*. The mean error is 14.2% ($\approx$0.4m) lower, the standard deviation smaller and the maximum error was reduced by $\approx$3.4m. But

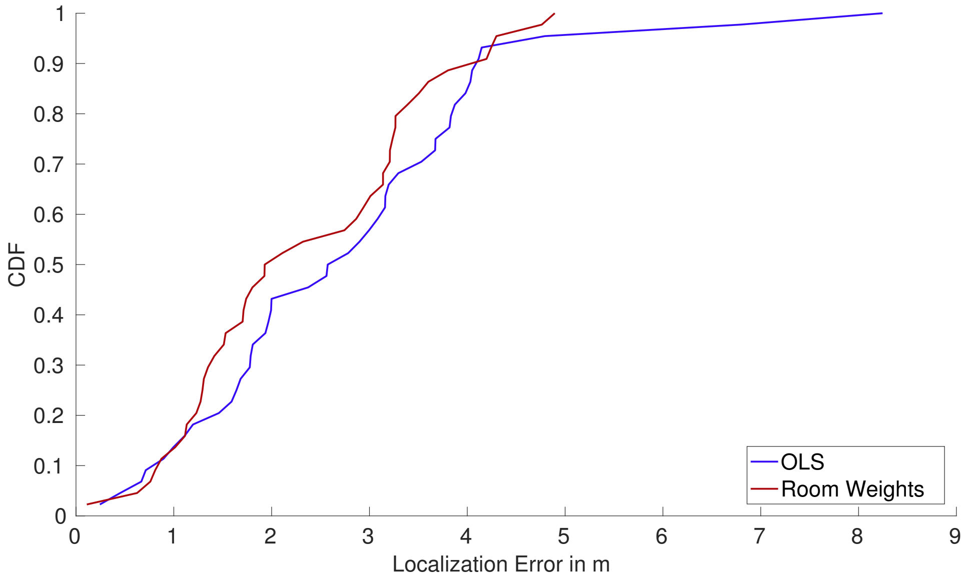

FIGURE 5.2: The Localization error with the *Room Weights*.

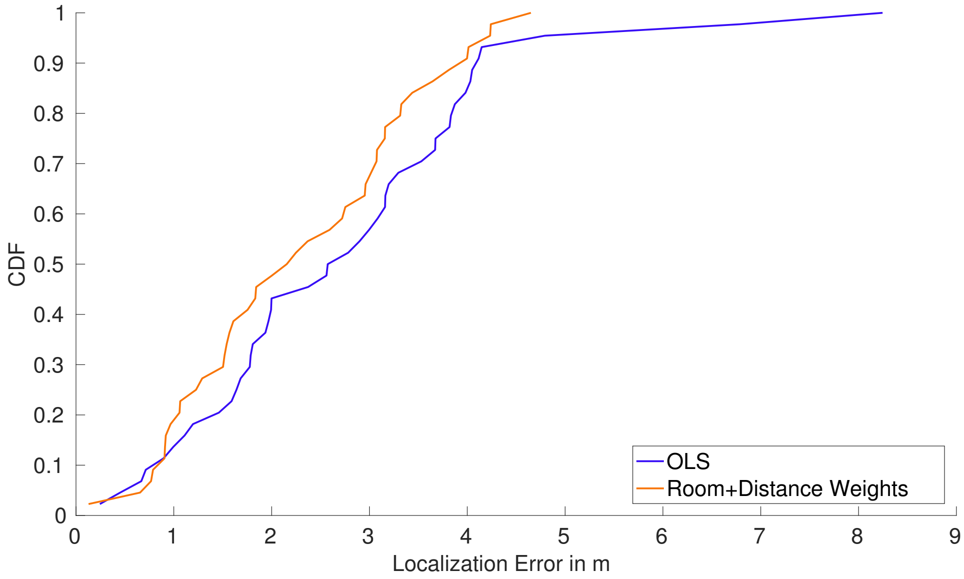

FIGURE 5.3: The Localization error with the *combined room and distance weights*.

when looking at the CDF plot (figure: 5.2) the improvement, although visible, does not seem very dramatic and is mainly due to the large reduction in the maximum error.

The results also show that combining the *Room* and *Distance Weights* does indeed yield a further small improvement. While the mean error is only marginally increased, it lowers the maximum error even further and smooths out the CDF curve (figure: 5.3).

The comparison between the performance of the weighting in a best case scenario and real world case, shows that there is indeed a error introduced by the room recognition. But the CDF (figure: 5.4) shows that this error is overall very small and mainly due to a few samples with a large error, which increase the maximum error.

However when taking into account this error, the real world performance of the proposed weighting method is almost the same as the existing simpler *Distance Weights*. This is apparent in figure 5.5. The mean error is only a few centimetres lower (0.07m) and the maximum error even higher than with the *Distance Weights*.

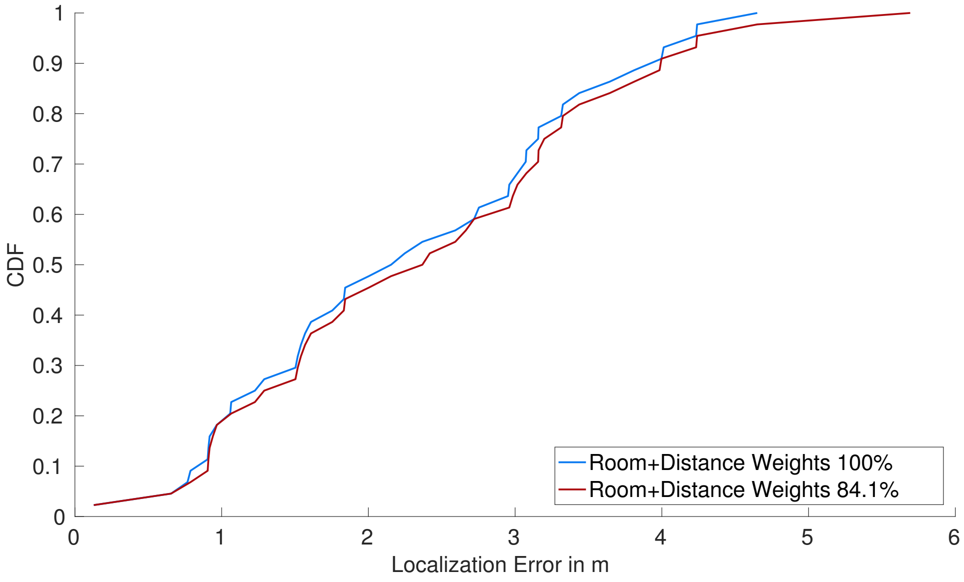

FIGURE 5.4: Localization error with *combined room and distance weights* in a best-case and real world scenario

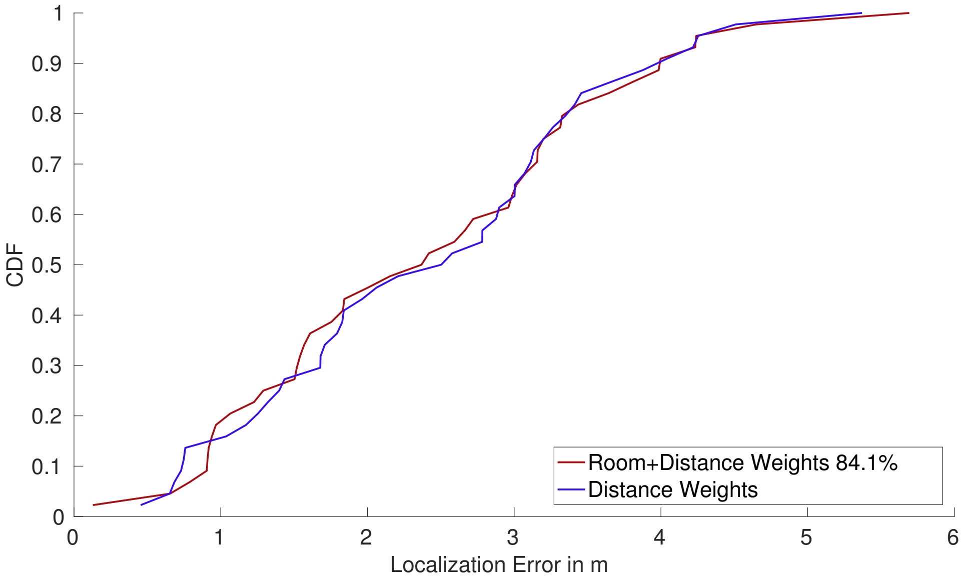

FIGURE 5.5: Localization error for the *combined room and distance weights* and *Distance Weights*

Chapter 6

Conclusion

6.1 Summary

Indoor localization remains a challenging problem in computer science.

In this thesis I combine the two most common localization approaches into one system; Adding a room recognition system to a range based approach to improve the trilateration weights and the localisation accuracy.

I propose a room recognition system based on fingerprinting with RSSI and magnetic field data and a new weighting method for range based localization by defining a set of weights for each room.

The proposed system was then implemented in a test bed on a floor of the university building. Several experiment were carried out to evaluate the performance of the room recognition and weighting method.

6.2 Conclusion

Concerning the Room Recognition: Room recognition based on RSSI and magnetic field data is able to achieve a high accuracy, even with very small set of training data. The system is able to achieve *80-90% accuracy* depending on the size of the training data set.

The inclusion of magnetic field data *generally improves the room recognition accuracy by 10%*. However this improvement may be influenced by large temporary disruptions in the magnetic field.

The results indicate that there is no benefit of having a training data set with more samples at the borders. The best results, in comparison to the numbers of samples, are achieved with a *evenly distributed set of samples*.

For the SVM configuration the polynomial kernel seems to be the better suited kernel function.

Concerning the weighting: The proposed weighting method does work, and improve the accuracy compared to *OLS*. However the improvements are not very large. This can be explained by the fact that the NLR-model used for ranging already takes into account some environmental parameters.

Compared to already existing simpler *Distance Weight* the proposed method performs almost the same. Considering the added complexity and effort in collecting the room recognition samples the proposed weighting method is not practical. It does make more sense to use the *Distance Weights* instead.

6.2.1 Possible future work

Although the room recognition was not able to significantly improve the weighting, there are many other possible applications for a simple and effective room recognition system. As an example it could be included into a particle filter to enhance tracking performance for indoor tracking applications.

It would also be interesting to explore other ways to include magnetic filed data into indoor localization systems.

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