Wireless Sensor Networks for Received Signal Strength-Based Target Localization and Tracking with Kalman Filter Data Processing

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ABSTRACT OF THE
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Localization and tracking different targets have been and still are an important part of human society. There are countless ways to Locating and tracking targets. Each of them has their own advantages and disadvantages. In this thesis the received signal strength indicator -based locating and tracking techniques are explored. Received signal strength indicator is based on radio wave power decreasing inversely proportional to travelled distances square. Usually, radio waves power is measured in decibels, thus converting the travelled distance squared to logarithm of the travelled distance. Received signal strength indicator can be measured with a wireless sensor network. A wireless sensor network is a measurement cluster powered by small, independent, self-organizing, battery-powered nodes. In a wireless sensor network, there are two types of nodes. So called measurement nodes which measure the environment, and anchor nodes which estimate their own position. If something from the trackable target's movement modes is known, with the Kalman filter the measured data can be filtered.
For this thesis, a simulation of a radio wave power decreasing in 100 meters by 100 meters room was created, to study the effects of anchor node count and positioning. Furthermore, the effectiveness of Kalman filter is briefly demonstrated in this thesis.

Keywords: RSSI, Bayesian filter, Kalman filter

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Sijainnin tarkka määrittäminen on ollut tärkeää kautta aikojen. Tarkka sijainti voidaan määrittää käyttämällä langatonta anturiverkkoa. Anturiverkot ovat kustannustehokkaita mittausverkkoja, jotka koostuvat solmuista eli noodeista. Solmut ovat pieniä, noin kolikon kokoisia tietokoneita, joissa on antureita. Tavallisessa anturiverkossa on useita anturisolmuja ja muutamia ankkurisolmuja. Anturisolmut mittaavat erinäisiä ympäristössä tapahtuvia asioita ja ilmiöitä. Ankkurisolmut puolestaan ovat erikoistuneet oman sijaintinsa määrittämiseen. Ankkurisolmu voidaan esimerkiksi asentaa tunnettuun sijaintiin, tai ankkurisolmussa voi olla asennettuna jokin sijainnin määrittämiseen erikoistunut anturi. Näiden ankkurisolmujen avulla on mahdollista määrittää anturisolmujen sijainnit. Lisäksi anturiverkolla voidaan määrittää muiden sen toiminta-alueella sijaitsevien esineiden sijainnit. Koska anturiverkon anturisolmut ovat yleensä pieniä, niihin ei mahdu paljoa tekniikkaa. Tämän takia anturisolmuissa ei yleensä ole erillistä sijaintiin erikoistuvaa anturia. Kaikki anturiverkon solmut tarvitsevat yhteydenpitolaitteen, jotta niiden keräämää informaatiota olisi mahdollista hyödyntää.
Yleensä yhteydenpitolaitteet lähettävät ja vastaanottavat radiosignaaleja. Radiosignaalien teho on kääntäen verrannollinen etäisyyden neliöön. Yleensä radiosignaalien heikkenemistä kuvataan Friisin siirtoyhtälöllä, jota hyödyntämällä voidaan laskea etäisyys ankkurisolmun ja anturisolmun välillä. Jos anturisolmusta saadaan mitattua etäisyys kolmeen tai useampaan ankkurisolmun, voidaan anturisolmun sijainti laskea hyödyntäen trilaterointia.
Sisätilat ovat erinomainen käyttökohde radiosignaalien vahvuuteen perustuvaan sijainnin määrittämiseen, sillä tunnetuimmat sijainnin määrittämistavat, kuten maailmanlaajuisen paikallistamisjärjestelmän käyttäminen, eivät toimi sisätiloissa. Valitettavasti radiosignaalien vahvuuteen perustuva sijainnin määrittäminen sisätiloissa ei ole aivan suoraviivaista. Radiosignaalit esimerkiksi kimpoavat seinistä ja aiheuttavat kohinaa antureihin. Myös muut samalla radiotaajuudella toimivat laitteet aiheuttavat kohinaa antureihin. Kohinaa voidaan pienentää, jos tiedetään mielenkiinnon kohteena olevan esineen sijainnin tilamalli ja tiedetään, että mittausdatan kohina on nolla keskiarvoista ja se seuraa gaussista todennäköisyysjakaumaa. Tähän on kehitetty niin kutsuttu Kalman suodatin, jota käyttämällä voidaan parantaa sijainnin tarkkuutta.

Työssä tehtiin simulaatio, jonka avulla arvioitiin radioaaltojen tehon vaimenemiseen perustuvan paikannus- ja seurantamenetelmän toimivuutta. Lisäksi simulaatiossa tutkittiin Kalman-suodattimen kykyä suodattaa kohinaisia tehon mittauksia. Ensin simulaatio loi yksinkertaisen reitin, jota pitkin kohde liikkui. Seuraavaksi simulaatio laski jokaisen reitin askeleen etäisyydet kaikkiin akkurisolmuihin ja tämän perusteella laski kunkin ankkurisolmun vastaanottaman radiosignaalin tehon. Tämän jälkeen simulaatio lisäsi tehon mittauksiin kohinaa. Viimeiseksi simulaatio laski kohinaisesta tehosta kohteen arvioidun reitin ja vertasi tätä oikeaan reittiin. Lopuksi simulaatio suodatti kohinaisen sijaintidatan Kalman-suodattimella ja vertasi tätäkin oikeaan reittiin.

Avainsanat: RSSI, Bayesian suodatin, Kalman suodatin

Contents

Abbreviations

RSSI received signal strength indicator 3

L&T localization and tracking 1

WSN wireless sensor network 1

AoA angle of approach 3

CPU central processing unit 1

GPS global positioning system 1

ToA time of arrival 3

TDoA time difference of arrival 3

KF Kalman filter 3

UKF unscented Kalman filter 6

EKF extended Kalman filter 6

RFID radio-frequency identification 4

RF radio frequency 4

IR infra red 4

BLE Bluetooth low energy 4

LNSFM log normal shadow fading model 8

RMSE root mean square error 13

1 Introduction

1.1 Wireless sensor networks

Wireless sensor network (WSN) are large, self-organized networks of small, low-cost, battery-powered, and wireless computing nodes gathering data from their surroundings. General WSN nodes have a central processing unit (CPU) for simple data processing, radio for communicating with nearby nodes and with the sink node, sensors for gathering useful information, and a battery for remote operation. Usually most of the nodes are randomly deployed close to the point of interest. WSN have a base station, or a sink, to which the nodes transfer raw or slightly precomputed data [1]. The sink node usually is equipped with more computing power than other nodes and is used to further compute the data and transfer it to worldwide use. A problem with WSNs is that usually the nodes are randomly positioned. Collected data is in most cases not useful if the location where the data is gathered is not known.

A WSN can be used for localization and tracking (L&T) targets. In a WSN, newly added or moving node positions are required to be determined. WSN usually has a few anchor nodes whose positions are known and can be used to determine the positions of the non-anchor nodes. There are multiple ways to L&T a node, which all have their pros and cons. One of the best-known L&T systems is the United States of America global positioning system (GPS), which is able to locate almost anything on the Earth in a few meters accuracy [1]. The GPS also has drawbacks. For example, it only works when you have a clear line of sight to the satellites. In many indoor locations this is not the case, thus GPS can not be used. Furthermore, GPS ability to only L&T objects in a few meters is not enough. Lastly, one of the most important drawback disadvantages of GPS is that it requires a dedicated chip in the system to function. Adding one additional chip into a system might not seem like a problem, but when considering that the nodes in WSNs are usually about the size of a coin, inserting a new extra chip becomes a lot harder. For these reasons one might want to L&T nodes with the node's communication unit, which are already installed for data transmitting purposes [1].

1.2 Different use cases for WSNs

A WSN has a broad definition, thus allowing it to be used in a wide variety of applications ranging from military uses to home appliances [1].

In military settings, WSN can be easily deployed to enemy territory, due to nodes' small and wireless nature. For instance, it can be used to monitor different phenomena in enemy territory. For example, they can be used to track and intercept radio signals to get information about the strategies of the enemy. In addition, it can also be utilized to disturb the radio communications of the enemy [1]. On the defending side, WSNs can be deployed to L&T equipment and people. Furthermore, WSNs can monitor different radioactive, biological, and chemical phenomena in the field.

The monitoring capability of the WSNs can be utilized to gather information from different natural phenomena for research purposes. For example, WSN nodes can be deployed into forests to detect fires or pollution levels. Furthermore, WSN nodes can be thrown into hurricanes or other natural phenomena, which need to be further researched [1].

2 Background

Target L&T has been an area of interest for many years and still is. Most of the time, it is important to know the location of the sensor, to utilize the data which the sensor has gathered. The first part of this chapter focuses on the different types of L&T. The second part focuses on the different types of Wireless indoors techniques and the third part focus on the Kalman filter (KF).

2.1 Different types of L&T

The L&T methods are separated into two main categories: range-based and range-free L&T techniques. Range-free algorithm's accuracy is typically low compared to the range-based counterparts [1]. Range-based methods measure the distance between the node and anchors to L&T the node. Utilizing the distances, one can, with trilateration, find the nodes position. Jondhale *et al.* [1] list four main types of range-based L&T methods: time of arrival (ToA), angle of approach (AoA), received signal strength indicator (RSSI) and the time difference of arrival (TDoA). In the following sections these methods are discussed.

2.1.1 AoA based L&T

The AoA based approach utilizes the angles between the node and anchors to find the distances between these two. Angles are measured using an array of directional antennas [5]. This poses a space constraint inside the node. Limited space poses a challenge in a node scarcely larger than a coin.

2.1.2 ToA and TDoA based L&T

Both ToA and TDoA utilize a clock and the known velocity of the wave to calculate the distances between node and anchors. Usually the CPU has a built-in clock, but it is often unreliable [7]. For this reason, solutions based on ToA and TDoA typically incorporate an external clock chip, which imposes the same space constraints as with the other methods [1]. Further the clock on the node and the clock on the anchor node need to be synchronized. The clock's desyncing causes problems with the distance calculations.

2.1.3 RSSI based L&T

The RSSI based approach utilizes the magnitude of the power of the received signal. RSSI measurements can be obtained through the radio communication unit, thus not requiring additional hardware to be installed.

Unlike the above-mentioned methods, RSSI does not either require an additional chip to be installed or a synchronization between the node and anchors clocks, thus being the easiest to utilize into a WSN node [1]. In contrast, an RSSI based approach is required to store more information on its surroundings compared to the other. For example, for RSSI approach to function it is required to store the transmitting and receiving antenna gains, operating frequency and transmitted and received signal powers [1]. Only the received signal power can be measured using the equipment on the node. Furthermore, the RSSI approach requires more computing power to store and utilize these additional data points.

Lastly, one of the biggest problems with the RSSI based approach is the low accuracy of the method, which is usually above 1 meter. The poor accuracy is due to many unpleasant properties of the indoor space. For example, signals bounce from the walls and other decoration elements inside, creating noise to RSSI data [1]. Furthermore, the accuracy in which the RSSI is measured, greatly affects the L&T accuracy.

2.2 Different types of Wireless indoors L&T

The measurements for above mentioned L&T techniques can be obtained utilizing different types of sensors. For example, one can utilize radio frequency (RF), acoustics or infra red (IR)-based sensors for this [2]. Unfortunately, acoustics and IR based methods require an additional chip to be installed, so these ran into the same space constraint in the small chip which are already mentioned above.

2.2.1 RF based L&T approaches

The RF based techniques differ only by the frequency with which they operate. Different frequencies pose multiple pros and cons to the usage, thus having their own use cases and names. radio-frequency identification (RFID), WiFi, Bluetooth and Zigbee are a few examples of these techniques.

WiFi as defined by the IEEE 802.11 standard is one of best-known wireless technologies. One might assume that WiFi based L&T approaches would be the easiest to utilize in real life, due to the WiFis popularity in our everyday equipment and due to WiFis communication range being up to 100 m. Unfortunately, WiFi also has multiple drawbacks. Firstly, WiFi is designed to be used for data communication purposes, not for a L&T purposes. This increases the power consumption of the communication unit. Secondly, the accuracy of WiFi based L&T is around 2 m, which is low for some use cases. This low accuracy is due to the signal variations [1].

Bluetooth as defined in the IEEE 802.15.1 standard is also a well-known wireless technology. The modern version of Bluetooth is the Bluetooth low energy (BLE).

It is installed in many smart devices and is used extensively in L&T objects in the world. This is partly due to its low power consumption and high data rate [1]. For example, Apple's AirTag network utilizes BLE to L&T iPhones [8].

On the other hand, RFID as defined in the IEEE 802.15 standard is a less known wireless technology. There are two types of RFID utilizations. So-called active utilizations require a battery and a CPU to send messages between the anchor and the node [1]. So-called passive utilizations do not require a battery and are operated solely by the anchor. Unfortunately, the communication range of RFID is only 5 m which is not long enough to L&T targets in a bigger indoor space.

Zigbee is defined in the IEEE 802.15.4 standard. It works on the 2.4GHz range which is unlicensed [1]. Zigbees communication range is about 30 m, which is a bit short but works in smaller office spaces. Furthermore, its power consumption is low. Unfortunately, Zigbee is susceptible to outside influences, and it is not available in many wireless devices. Still the interest in Zigbee has grown in the research community [1].

2.2.2 Acoustic based L&T approach

Acoustic L&T approaches share many similarities with RF-based approaches. Liu *et al.* [6] even argues that many acoustic L&T methods are borrowed from the RF approaches [6]. In cases of the time based L&T algorithm, acoustics might be superior compared to the RF counterparts. This is due to the acoustic waves traveling a few magnitudes lower speed compared to RF waves. This allows more error tolerance for the measurement equipment. Furthermore, Acoustic waves can be picked up by ordinary microphones, which are already widely utilized in devices [6].

Acoustic L&T approaches also have a few drawbacks. Liu *et al.* [6] lists a few examples of these drawbacks. Firstly the signal to noise ratio in acoustic measurements is low and secondly the acoustic signals echo out of walls and other household objects.

2.3 The Kalman Filter

Due to the noisy nature of RSSI measurements, a filter which optimizes the results would be handy. R. Kalman published a revolutionary paper in 1960 [3], in which he described a recursive solution to a discrete-time linear optimization problem. In literature this solution is known as the KF. The recursive part of the solution allows the KF to utilize history on its state estimations without wasting vast amounts of memory. To work the KF requires the system to be linear and the noise in the measurements must follow Gaussian distribution with zero mean.

The KF works in cycles of data prediction and value updating [1]. In the prediction step the KF tries to estimate the next state of systems utilizing the known state-transition matrix. In the updating step the filter compares the estimated values to the measured values.

In practice the requirements for KF are rarely met [4]. For this reason researchers have created so-called extended Kalman filter (EKF) and unscented Kalman filter (UKF) [1]. The UKF was the first filtering system which worked on non-linear systems. It was based on the numerical integration approximation of the motion system. The EKF works on the assumption that non-gaussian noises can be estimated as Gaussian distributions and the UKF.

2.4 Summary

There are many ways to L&T targets. Most of these are done with RF signals. Some techniques work with acoustic signals, but in this thesis those methods are not studied. Most of these require an external sensor or a clock to function. RSSI can be measured with the devices communication unit, which is anyways required. With RSSI, the distance between the device and the anchor can be estimated. WIth KF the measured data can be filtered.

3 Method

In this chapter the mathematical basics of the phenomena described in the background section are shown.

3.1 RSSI equations

As mentioned in the background section 2.1.3, RSSI based approaches utilize the magnitude of the power of the received signal to determine the distance between nodes. The power can be measured utilizing the communication unit. The equation which can calculate the distance from the RSSI power measurements is called the Friis transmission formula [1]. It uses the transmitter gains, light wavelength, and the distance between targets to calculate the relation between power delivered from the transmit antenna and the power measured in the receiving antenna. If one knows the transmit power, then this formula can be used to calculate the received power. The equation can be described as following:

$$\frac{P_r}{P_t} = G_t G_r \left(\frac{\lambda}{2\pi d}\right)^2, \tag{3.1}$$

where P_r is the power measured in the node, P_t is the power transmitted from the anchor node, G_t is the transmitter antenna gain, G_r is the receiver antenna gain, d is the distance between the node and anchor, and λ is the wavelength of the transmitter signal. From the equation 3.1 we can solve the P_r, if the P_t is known:

$$P_r = P_t G_t G_r \left(\frac{\lambda}{2\pi d}\right)^2, \tag{3.2}$$

In this equation P_r is not given in decibels, but in practice the P_r measurements are usually given in decibels. The equation 3.2 can be rewritten as following in decibels:

$$P_r^{[dB]} = P_t^{[dB]} + G_t^{[dB]} + G_r^{[dB]} + 20\log_{10}\left(\frac{\lambda}{2\pi d}\right), \tag{3.3}$$

where $P_r^{[dB]}$ is the power measured in the node in decibels, $P_t^{[dB]}$ is the power transmitted from the anchor node in decibels, $G_t^{[dB]}$ is the transmitter antenna gain in decibels, $G_t^{[dB]}$ is the receiver antenna gain in decibels, d is the distance between the node in meters and anchor, and λ is the wavelength of the transmitter signal.

The variable of interest is the distance d. It can be solved from the equation 3.3. The equation for the distance d is as following:

$$d = \frac{\lambda}{4\pi} 10^{-\frac{P_r^{[dB]} - P_t^{[dB]} - G_t^{[dB]} - G_r^{[dB]}}{20}}. \tag{3.4}$$

3.2 Log Normal Shadow Fading Model

With Friis transmission formula, the RSSI can be approximated. Log normal shadow fading model (LNSFM) is the next version of Friis model [1]. The formula for RSSI with LNSFM can be given as the following:

$$P_r^{[dB]} = P_{r0}^{[dB]} - 10\eta \log\left(\frac{d}{d_0}\right), \tag{3.5}$$

where $P_r^{[dB]}$ is received power at distance d, $P_{r0}^{[dB]}$ is received power at distance d_0, d_0 is reference distance, d is distance between antennas and η is path loss exponent.

3.3 Trilateration

If one knows nodes distance from three or more known locations, the location of the points can be obtained with a technique called trilateration. In this thesis the distances are measured with the RSSI. Other ways to measure this distance are described in the backgrounds section 2.1.

Jondhale *et al.* [1] shows the following equations to calculate the position from these measurements:

$$x = \frac{AY_{32} + BY_13 + CY_21}{2\left(x_1Y_{32} + x_2Y_{13} + x_3Y_21\right)}, y = \frac{AX_{32} + BX_{13} + CX_{21}}{2\left(y_1X_{32} + y_2X_{13} + y_3X_21\right)}, \tag{3.6}$$

in which

$$A = x_1^2 + y_1^2 - d_1^2, B = x_2^2 + y_2^2 - d_2^2, C = x_3^2 + y_3^2 - d_3^2, \tag{3.7}$$

$$X_{32} = (x_3 - x_2), X_{13} = (x_1 - x_3), X_{21} = (x_2 - x_1), \tag{3.8}$$

$$Y_{32} = (y_3 - y_2), Y_{13} = (y_1 - y_3), Y_{21} = (y_2 - y_1), \tag{3.9}$$

where the x_n is the position of the nth node in X-axis and y_n is the position of the nth node in Y-axis

3.4 Constant velocity model

If one knows about the state model of the target we can improve the accuracy of our state estimates. In this study, it is assumed that the target is moving at constant velocity. The state of the target can be represented as following:

$$X_k = \begin{bmatrix} x_k \\ y_k \\ \dot{x}_k \\ \dot{y}_k \end{bmatrix}. \tag{3.10}$$

The simple state model can be represented as following:

$$X_k = AX_{k-1} + q_{k-1} \tag{3.11}$$

where the A matrix is the following:

$$A = \begin{bmatrix} 1 & 0 & T_s & 0 \\ 0 & 1 & 0 & T_s \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \tag{3.12}$$

the T_s is the time for one emulation-step and q_i represents system noise.

The actual position Y_k can be obtained from the states with the following measurement model:

$$Y_k = HX_k, \tag{3.13}$$

where the Y_k is the following:

$$Y_k = \begin{bmatrix} x_k \\ y_k \end{bmatrix}, \tag{3.14}$$

and H is the following:

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}. \tag{3.15}$$

3.5 Kalman Filter

In this subsection, the KF is explained. All of the following contents are based on the Jondhale *et al.* book [1].

As explained in the background section 2.3, KF can be used to improve the accuracy of linear systems calculations. As said, KF works in two parts. The first part is the prediction step which consists of predicting the next state $\bar{X}_k$ and updating the temporary covariance matrix P_k^-. The equation for the state prediction can be given as following

$$\bar{X}_k = A\hat{X}_{k-1}, \tag{3.16}$$

where A is the same state-transition matrix as in equation 3.12 and the $\hat{X}_{k-1}$ is the previous state estimation.

The temporary covariance matrix P_k^- update can be written as the following.

$$P_k^- = AP_{k-1}A^T + Q_k. \tag{3.17}$$

The second part in the KF is the update part. In this part we calculate the Kalman gain matrix K_k, update the state estimation $\hat{X}_k$ and calculate the new covariance matrix P_k.

Kalman gain K_k is calculated by the following formula:

$$K_k = P_k^- H^T \left(H P_k^- H^T + R \right)^{-1}. \tag{3.18}$$

Utilizing the Kalman gain K_k and the measured position z_k, it is possible to increase the accuracy of state approximation $\hat{X}_k$.

$$\hat{X}_k = \bar{X}_k + K_k \left(z_k - H_k \bar{X}_k \right). \tag{3.19}$$

And the last step in KF is updating the covariance matrix P_k with the following equation

$$P_k = \left(I - K_k H_k \right) P_k^-. \tag{3.20}$$

Due to the relation between the current and the previous state estimation, KF is a recursive approach to linear optimization problem. As stated in the background, this reduces the memory usage of filtering.

3.6 Summary

The ratio between RSSI and distance can be modeled with either the Friis equations, or if a better estimate is required, it can be estimated with the LNSFM. If RSSI measurements are available from three or more anchor nodes, the position of the node can be estimated with trilateration. KF can be used to filter the noisy measured RSSI data.

4 Results

In this chapter first, the synthetic data creation is explained secondly, the results of this study with just trilateration are represented and in the third and last part the results with just the trilateration are compared to the results with the KF.

4.1 Creating synthetic data

First, a trajectory of our target is created. The actual trajectory of the target is depicted as blue polylines and positions of anchor nodes are depicted as the black dots on the corners of the Figure 1. In this study, the simulated experiment room is 100 meters by 100 meters, and the anchor nodes are located on the corners of the room. In the next chapter the effects of anchor positioning are shown. Secondly, the distances from each step of trajectory to all anchor nodes are calculated. This can be easily done with the help of the Pythagorean theorem. In the Figure 2a the distances of each step of the trajectory to each anchor node are represented.

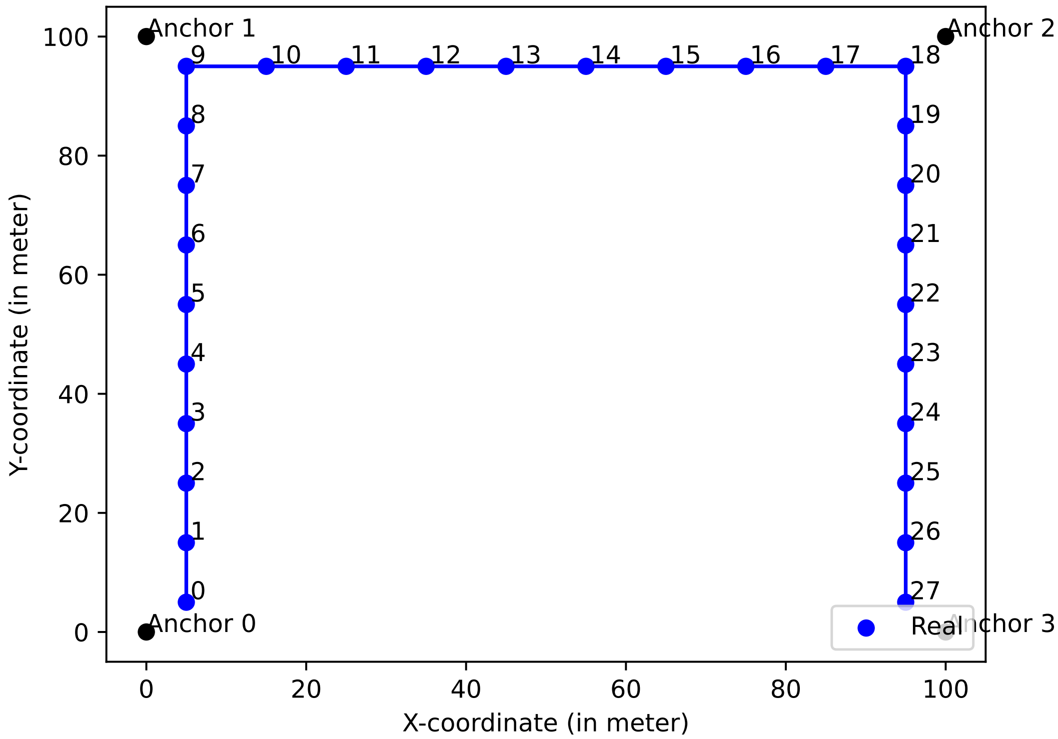
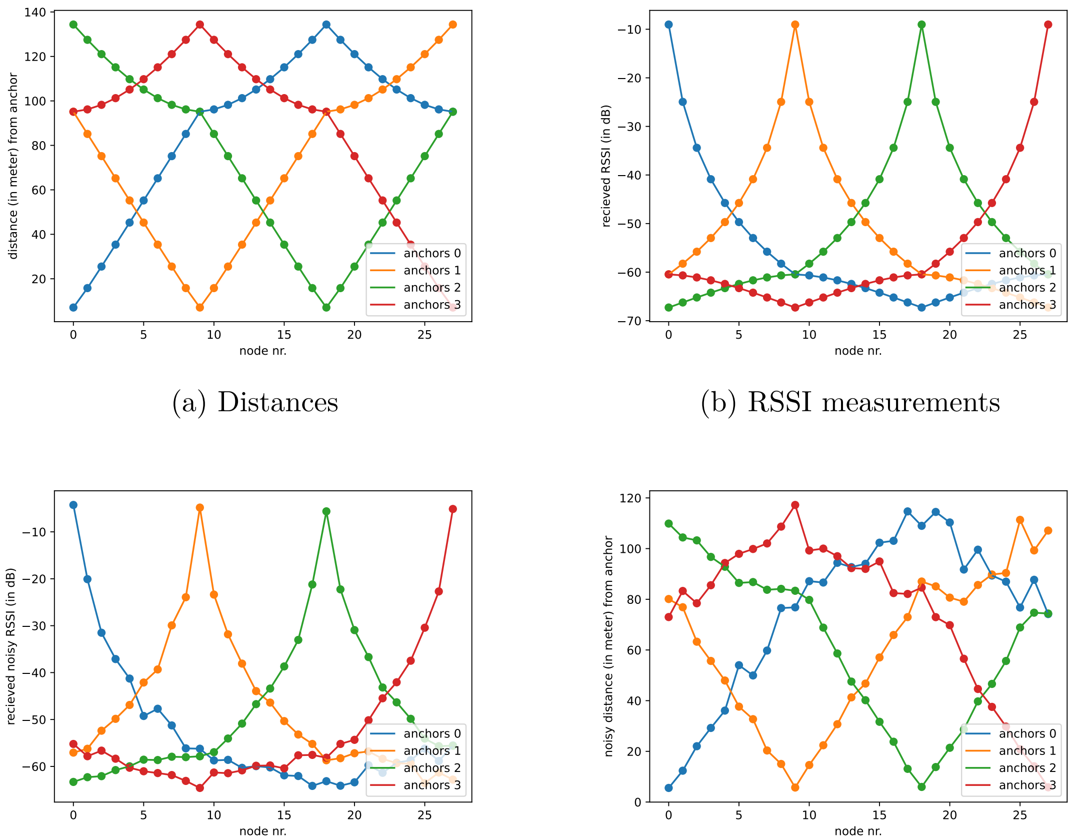


Figure 1: Target Trajectory

The third step of the process is to convert the distances to RSSI measurements. The RSSI measurements are calculated using LNSFM, which is described in detail in equation 3.5. In the 2b the RSSI measurements of each step of trajectory to each anchor node are represented.

The fourth step is to add some white gaussian noise to our RSSI measurements. The noisy RSSI measurements are readings which can be measured using real world equipment. In the Figure 2c the noisy RSSI measurements of each step of trajectory to each anchor node are represented.

Next when the synthetic noisy RSSI data is generated, the accuracy of RSSI L&T can be determined. First, the noisy RSSI data is required to be converted into position data. First step of this process is to convert the RSSI readings back to distances. This can be achieved by solving the distance from LNSFM equation 3.5. In the Figure 2d the noisy distance readings are presented.



(a) Distances

(b) RSSI measurements

(c) Noisy RSSI measurements

(d) Noisy distances

Figure 2: Figure presenting RSSI and distance reading

And lastly the distances can be trilaterated, which is described in detail in subsection 3.3, into 2d-coordinates. Figure 3 shows the estimated trajectory of the target.

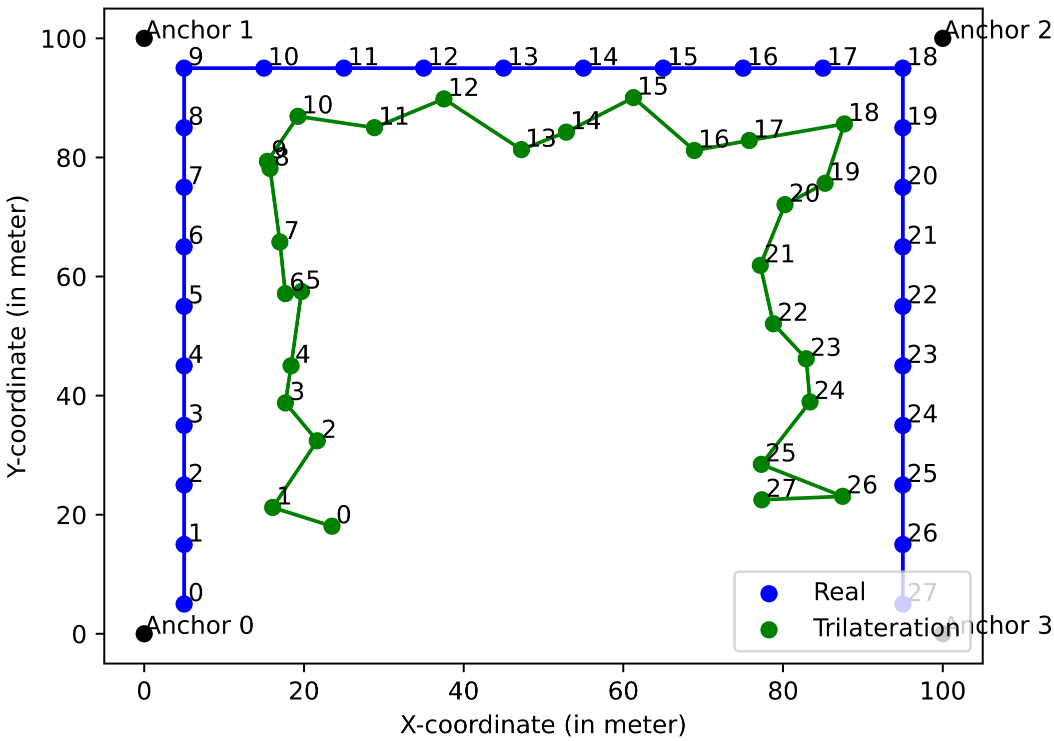


Figure 3: Noisy distances

4.2 Evaluating the results

To each result of this study, a root mean square error (RMSE) value has been assigned. RMSE is a simple way to grade results. In it the mean between the measurements and the real data points is calculated, with the formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2}{2N}}, \tag{4.1}$$

where $\hat{x}_i$ is the ith estimated position in x-axis, x_i is the ith actual point in the x-axis, $\hat{y}_i$ is the ith estimated position in y-axis, y_i is the ith actual point in y-axis and N represent the number of points in our dataset.

4.3 LT using only Trilateration

In the last section, the process of creating synthetic data was explained. There are multiple ways of improving trajectory estimation. This section shows the effects of the location and number of anchor nodes. In these results, the measurement noise is set to 3 dB.

4.3.1 Effects of number of anchors

In the previous subsection's example position of the anchor nodes, the RMSE was approximately 10.01 meters. With this accuracy it is hard to locate anything in a room. One reason for this inaccuracy is the radio signals range. As explained in the background section WiFi is the farthest-reaching radio frequency standard, but even has short range, approximately 100 meters [1].

An effortless way to improve the accuracy of RSSI based L&T is to add an anchor node in the middle of the room. With this straightforward improvement the accuracy dropped to 6.09 meters. The Figure 4 shows how the anchor nodes are positioned.

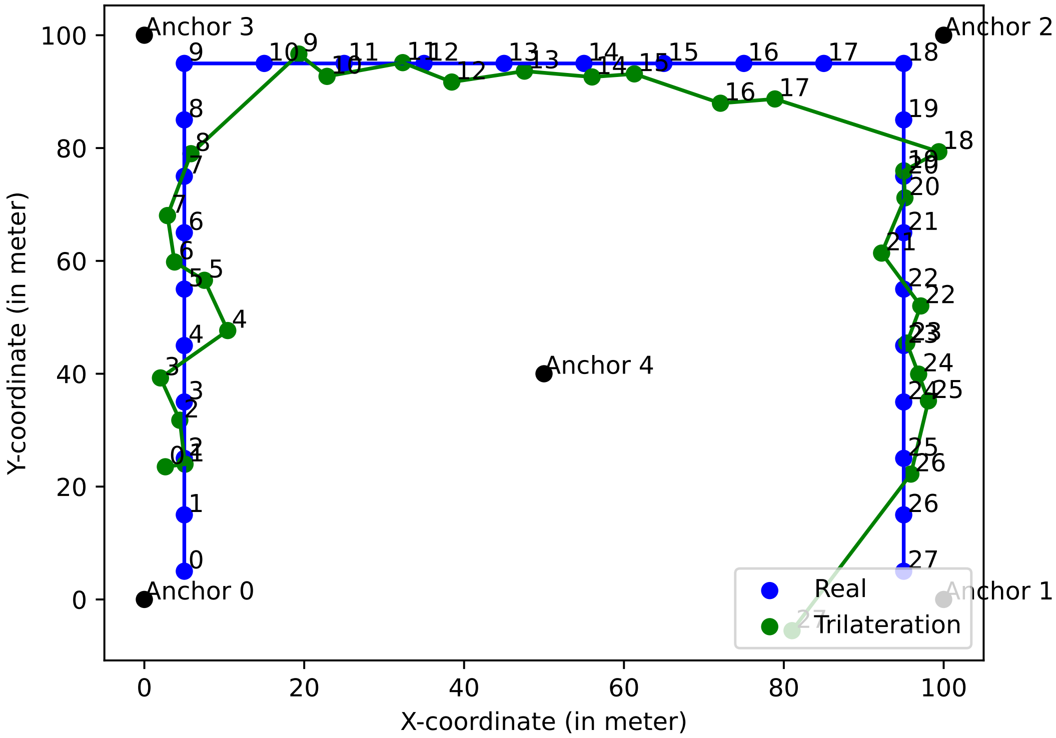


Figure 4: Setup with five anchors

Increasing the anchor node count even further the same trend occurs. For example, with 8 anchor nodes the RMSE drops down to 4.82 meters and with 16 anchor nodes the RMSE drops to 2.99 meters. In the Figure 5 the setup with 16 anchor nodes is presented.

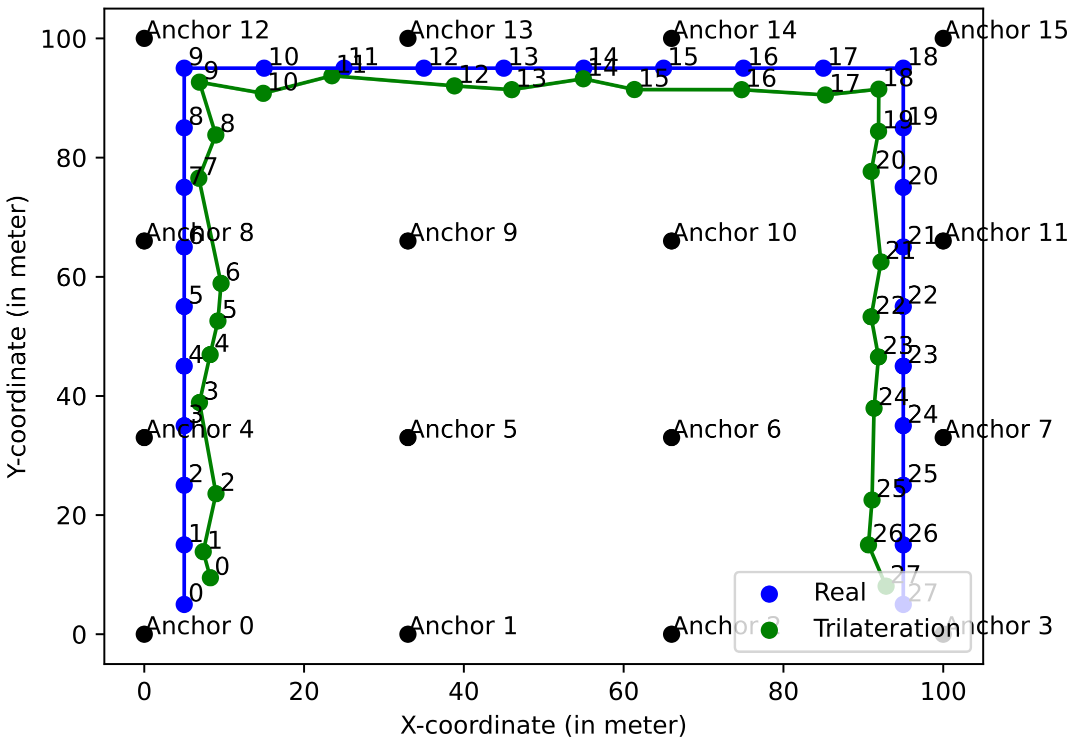


Figure 5: Setup with 16 anchors

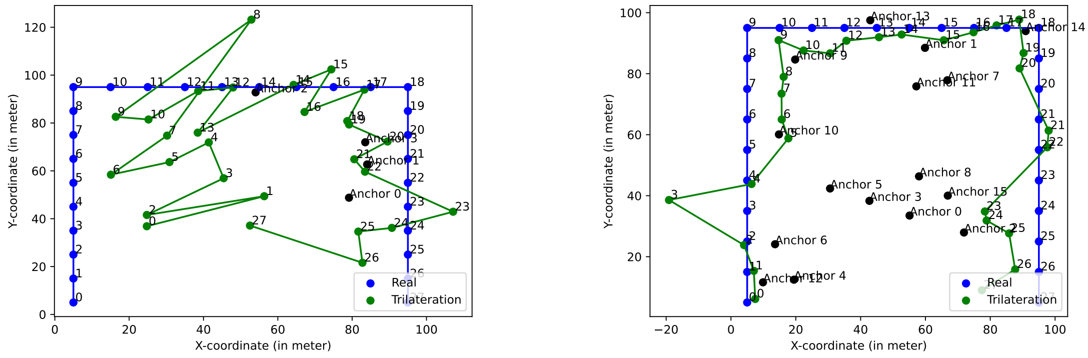
4.3.2 Effects of anchor positioning

In the previous subsections examples, anchor node positions have been carefully. In real world settings the anchor nodes are usually deployed in random positions, thus not guaranteeing optimal anchor node layout. When deploying the four anchor nodes randomly into the room, one layout RMSE would increase the L&T accuracy up to 19.67 meters. In the Figure 6a this layout is presented. If the anchor node count is increased to 16, the accuracy drops down to 7.15 meters.

4.4 Improving LT using Kalman filter

While adding more anchor nodes, increases the accuracy of the L&T it also increases the cost of the L&T WSN. If some attributes of the movement model are known, the noise in the measurement data can be filtered with KF. In the case of this study, the target moves at a constant speed, thus allowing the KF to filter the measurements.

In the previously mentioned cases, KF slightly improved the L&T accuracy. For the four node scenario the L&T accuracy with KF drops down to 7.46 meters and with four randomly placed anchor nodes the L&T accuracy with KF drops down to



(a) Setup with four randomly positioned anchors

(b) Setup with 16 randomly positioned anchors

Table 1: Result with good anchor node placements

Anchor Count	RMSE without KF	RMSE with KF
4	10.01	7.46
5	5.92	4.49
8	4.55	3.26
9	4.2	3.49
16	2.99	2.59

12.34 meter. Rest of the measurements with optimal anchor positions are shown in the table 1 and rest of the measurements with optimal anchor positions are shown in the table 2. In the first column the number of anchor nodes is depicted, in the second column the RMSE with just trilateration are depicted and in the third column the RMSE with the KF are depicted.

Table 2: Result with random anchor node placements

Anchor Count	RMSE without KF	RMSE with KF
4	19.67	12.34
5	16.07	10.59
8	15.79	10.30
9	11.99	9.94
16	7.15	5.18

4.5 Conclusions

In this chapter the conclusions of this study are briefly discussed. As shown in the tables 1 and 2, it is viable to L&T targets with RSSI, if the application cares only for the approximated position of the target. If some properties of our target's movement model are known, the L&T accuracy can be slightly improved with KF. Greater L&T accuracy improvement is obtained by increasing the number of anchor nodes. Increasing the number of anchor nodes costs, so that needs to be considered when comparing the effectiveness of KF based accuracy improving versus just increasing the numbers of anchor nodes. Of course if one has the computing power to filter the measured data with KF, it is a cheap way to improve the L&T accuracy. The results shown in this thesis coincide with the results presented in the Jondhale *et al.* book [1].

4.6 Summary

As shown in the tables 1 and 2, in a 100 meter by 100 meter room, it is possible to L&T targets using RSSI based L&T. Unfortunately, with four-nodes the accuracy is not great. With 16 anchors the accuracy starts being usable. The KF can smooth the measurement data a bit, but the anchor node has a bigger impact on the estimated trajectories' correctness than the KF. Of course if one has the

5 Summary

L&T different targets have been and still are an important part of human society. There are countless ways to L&T targets. Each of them has their own advantages and disadvantages. In this thesis the a RSSI based L&T techniques are explored. RSSI is based on the fact that radio waves power decreases inversely proportional to travelled distances square. Usually, radio waves power is measured in decibels, thus converting the travelled distance squared to logarithm of the travelled distance [1]. RSSI can be measured with a WSN. WSN is a measurement cluster powered by small, independent, self-organizing, battery-powered nodes [1]. In a WSN there are two types of nodes. So called measurement nodes which measure the environment, and anchor nodes which estimate their own position. If something from the trackable target's movement modes is known, with the KF the measured data can be filtered.

For this thesis, a simulation of a radio wave power decreasing in 100 meters by 100 meters room was created, to study the effects of anchor node count and positioning. Furthermore, the effectiveness of KF is briefly demonstrated in this thesis.

In 100 meters by 100 meters room with four well positioned anchor nodes, the L&T RMSE is 10.01 meters. This increases to 7.46 when filtered with KF. This can be easily improved by increasing the anchor node count. When one anchor node is added into the middle of the room the RMSE of L&T drops down to 5.92 meters and with KF the RMSE drops down to 4.49. In indoor spaces the anchor nodes can be located into optimal positions, but in typical WSN settings all nodes are randomly positioned. When anchor nodes are randomly positioned, five anchor node scenarios L&T accuracy RMSE drops down to 16.07 meters.

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