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Indoor Positioning System based on Bluetooth Low Energy for Blind or Visually Impaired Users

Running on a smartphone application

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INFORMATION AND COMMUNICATION TECHNOLOGY

Indoor Positioning System based on Bluetooth Low Energy for Blind or Visually Impaired Users

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Master’s Thesis

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Abstract

Blind and visually impaired (BVI) users desire an indoor navigation tool that is inexpensive, convenient, and reliable. The purpose of this thesis is to examine the feasibility of using a smartphone as a platform for such a navigation tool.

A good navigation tool should have both a good positioning accuracy and a user-friendly interface. Thus, one focus of this thesis is to improve the performance of an indoor positioning systems running on smartphones, as compared to existing systems. Another focus is to customize this indoor positioning system specifically for BVI users.

The proposed indoor positioning system is based upon Bluetooth Low Energy (BLE). It consists of two parts: BLE beacons deployed in the user's environment and an Android phone which calculates its position and provides navigation assistance by audio and vibration.

Two versions of the positioning software were developed based on different algorithms. One version uses a hybrid technique combining triangulation and fingerprinting. This version achieves a positioning accuracy of 1.83 meter, and volunteers (blind-folded sighted people) took on average 91.7 seconds to complete a complex 12-meter route. The other version uses a proximity algorithm, thus it does not give as accurate positioning results. With this algorithm, a blind user was able to finish a route of 115 meters consisting of two different floors in a building including entering/exiting an elevator and multiple office doors in 4 minutes 48 seconds. The blind user found the product to be helpful and user-friendly.

Finally, we draw the conclusion that a smartphone can be a good platform for a BVI navigation tool, under the condition that the algorithm is proximity based and navigation utilizes *a priori* information about the environment. Another insight we gained is that we should put beacons on braille signs so that blind people can find them by using the navigation app.

Keywords:

RSSI-based indoor positioning, Bluetooth, smartphone, blind and visually impaired

Sammanfattning

Blinda och synskadade (BVI) användare önskar sej ett inomhus navigeringsverktyg som är billigt, bekvämt och pålitligt. Syftet med detta examensarbete var att undersöka möjligheten att med en smartphone och utplacerade fyrar/beacons ge en bra plattform för en inomhus navigeringsmetod.

Ett bra navigationsverktyg bör ha både en bra positioneringsnoggrannhet och ett användarvänligt gränssnitt. Således är ett fokus för detta arbete att förbättra prestanda för på ett inomhus positioneringssystem som körs på smartphones, jämfört med andra befintliga system. Ett annat fokus är att anpassa denna inomhus positioneringssystem för speciella BVI användare.

Det vidare utvecklade inomhuspositionering systemet bygger på Bluetooth Low Energy (BLE). Den består av två delar: BLE fyrar/beacons utplacerade i kontorsmiljön och en smartphone som beräknar sin position och ger navigeringshjälp av ljud/röst och vibrationer. Vi utformade två versioner av positionerings programvaran med olika algoritmer. En version använder en hybridteknik med triangulering och en med fingerprints. Det uppnår en positioneringsnoggrannhet som är <1,83 meter och den testades på tolv seende personer med bindel för ögonen. Det tog vid testet 91.7 sekunder i genomsnitt att utföra en komplex 12 meter lång bana. Den andra versionen använder en närhets-algoritm som inte ger ett specifikt positioneringsresultat. Med denna algoritm kunde en blind användare avsluta en rutt 115 meter bestående av två olika våningar från ingång i golvplanet samt ta en hiss och gå in på ett kontor och genom hela kontoret på 4 minuter och 48 sekunder. Den blinda användaren ansåg att navigeringsverktyget var både användbart och användarvänligt.

Slutligen, drar vi slutsatsen att en smartphone kan vara en bra plattform för ett BVI navigeringsverktyg och då under förutsättning att algoritmen tar med närhet/position och inomhusmiljöinformation för att ge bästa möjliga användbarthet. En annan insikt vi fått är att vi ska lägga fyrar på punktskrift tecken så att blinda kan hitta dem med hjälp av navigering app.

Nyckelord:

RSSI-baserade inomhuspositionering, Bluetooth, smartphone, blinda och synskadade

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List of acronyms and abbreviations

AP	Access point
API	Application programming interface
AOA	Angle of arrival
BLE	Bluetooth Low Energy
BVI	Blind and visually impaired
CDF	Cumulative distribution function
PDF	Probability density function
PDR	Pedestrian dead reckoning
RSSI	Received-signal-strength-indicator
UI	User interface
TOA	Time of arrival
TDOA	Time difference of arrival
WHO	World Health Organization

1 Introduction

In this chapter, the background of indoor positioning is introduced and the motivation to design an indoor positioning system for the blind and visually impaired (BVI) on smartphones is justified. Sections 1.5 and 1.6 describe the research methodologies and delimitations (respectively) of this project. Section 1.7 presents the structure of the remainder of this thesis.

1.1 Background

There have been a great number of efforts to build indoor positioning and navigation systems. However, few of these systems have focused on navigation for BVI, despite the fact that this group could greatly benefit from such a system. According to the World Health Organization (WHO), 285 million people are estimated to be visually impaired worldwide, and about 90% of these people live in low-income settings [1]. In addition, among the existing navigation tools for the BVI, many are expensive and bulky; hence, they are frequently unaffordable and cause users to feel isolated from others. Today's smartphones are ubiquitous and inexpensive. They are easy to carry and unobtrusive. Most importantly, these smartphones are equipped with Bluetooth, Wi-Fi, and wide area cellular radio interfaces, along with a number of different types of sensors. As a result, these smartphones have an immense potential to support indoor navigation for the BVI.

Implementing an indoor positioning system is not easy. GPS is unavailable inside buildings because the line-of-sight condition is unfulfilled, thus people have turned to other methods: scene analysis, radio signal based systems, pedestrian dead reckoning, etc. Even after more than 20 years of research, indoor positioning remains an open challenge.

Guiding the BVI group is different from guiding sighted people. The system must not only achieve high positioning accuracy, but must also be a user-friendly navigation system. The requirements and preferences of BVI users are first studied. Based upon these requirements and preferences, an acoustic navigation system was designed, implemented (on an Android smartphone), and evaluated.

1.2 Problem definition

The problem is to evaluate whether a smartphone can be a good navigation tool for BVI users. Such a smartphone has limited processing capacity compared to desktop computers, a variety of inexpensive sensors, and one or more radio receivers with received-signal-strength-indicator (RSSI). More specifically, the problem is to design and implement an indoor positioning system running on a smartphone that is more cost-effective* and accurate than existing system based upon RSSI measurements and provides navigation guidance tailored for BVI users.

1.3 Purpose

The purpose of this project is to provide an indoor navigation solution running on a smartphone for BVI users. This new solution should provide additional assistance beyond the traditional solutions such as guide dogs and the white cane. As a result, BVI users should be able to achieve better mobility, independence, and autonomy.

* Note that "cost" can have various meanings. Refer to Section 3.7.5 for the meaning of cost in the context of this thesis.

1.4 Goals

The goal of this thesis project is to design, implement, and evaluate an indoor positioning system running on a smartphone for the BVI that provides a better solution than other systems using smartphones. Because I have chosen to make a system based upon RSSI, in order to get improved accuracy I have combined fingerprinting and trilateration positioning methods. Given this choice of position methods, I have divided the goal into three sub-goals:

1. Design and propose methods to reduce the cost of acquiring fingerprints and improve accuracy by combining fingerprinting and trilateration positioning methods,
2. Carry out experiments and measure the performance of a prototype indoor positioning system using the proposed methods, and
3. Design, implement, and evaluate an acoustic navigation system for BVI users that is tailored to their needs.

1.5 Research Methodology

In this project, both qualitative and quantitative research methodologies are used. Qualitative research was carried out to understand the requirements and preferences of the visually impaired, while quantitative research is performed to measure the performance of a prototype of the proposed system, according to the metrics described in Section 3.7.

1.6 Delimitations

Implementing the proposed system in a smart watch or a smart bracelet would make the hardware even easier to carry; however, this is outside the scope of this project.

1.7 Structure of the thesis

The remainder of this thesis is organized as follows. Chapter 2 presents relevant background information about the terms and techniques used in this project. Chapter 3 presents the methodology and method used to solve the problem proposed in Section 1.2. Chapter 4 describes the implementation and evaluation of the proposed indoor positioning system. Chapter 5 presents the results, analysis, and a comparison with existing indoor positioning systems. Chapter 6 concludes the thesis and suggests possible future directions for research on positioning systems for BVI users.

2 Background

This chapter first introduces Bluetooth technology and then explains why and how a system for BVI users should be designed. Following this is a review of existing indoor positioning techniques. We compared them and then justify our decision to implement a beacon-based system. Section 0 explains commonly used positioning methods, i.e., fingerprinting and triangulation. Additionally, this section describes post-process techniques, such as Kalman filtering and Hidden Markov Chains, as these techniques are frequently utilized to further improve positioning. Section 2.4 describes related work regarding existing indoor positioning systems that are similar and relevant to the needs of this project. Finally, the chapter closes with a short summary.

2.1 The Bluetooth Low Energy technology

Bluetooth technology is a standard enabling wireless connectivity of devices and operates in the unlicensed industrial, scientific, and medical (ISM) band at 2.4 to 2.485 GHz [2]. Bluetooth Low Energy (BLE) distinguishes itself from earlier versions of Bluetooth by its low energy consumption. This low energy consumption is achieved as no paired connection is required between two BLE devices when one is transmitting frames and the other receiving them [3]. A BLE beacon typically broadcasts at a certain interval frames that contain a unique identifier. An example of a commercial indoor positioning system is Tadlys Wireless Communications Ltd.'s TOPAZ which claims an average positioning accuracy of 2-3 meters and can locate tens of tags simultaneously, covering areas of thousands of square meters [4].

2.2 Needs and requirements of BVI users for an indoor navigation system

The paragraphs in this section are based upon an unpublished article (written by the author herself) entitled “The business model of an indoor positioning system”.

Today, a typical navigation system gives information in natural language. However, a product for BVI users should differ in the following aspects:

- Verbalization of audio messages

  Firstly, the audio guidance messages designed for the BVI should not be too detailed [5], as the BVI user “may find it difficult or impossible to attend to auditory outputs that occur while they are read” [6]. Fritz et al. interviewed blind and elderly people and concluded that the same user will require different levels of information in different situations, depending on how confident and familiar they are with the location and the route, thus users should have the ability to control the level of detail provided [7].

  Secondly, while audio guidance systems for sighted people usually give simple instructions such as “turn left” or ”walk straight", it will be challenging for the BVI user to follow these instructions exactly, as it is difficult for them to make perfect turns or move in straight lines [8]. Thus, the audio guidance system for BVI users should give information in a more continuous manner in order to help the user proceed in the correct direction.

  Thirdly, reference points should be used when describing a route to a BVI user. Nicolau et al. in their paper “*Blobby: How to guide a blind person*” [9] studied the way a BVI person communicates a route to a BVI colleague and found out that reference points are “the only way the BVI people have to build their mental map”, thus reference points are crucial. A reference point is some infrastructure element or other artifact that can easily be identified and cannot easily be moved. In fact, when a blind user is lost his/her first reaction is to turn back and try to find a reference point. Thus, reference points should be used in such navigation systems.

- Other stimuli

While natural language is widely used in many existing navigation systems for the BVI, some researchers proposed that spatialized audio is a better alternative. Spatialized audio enables the listener to perceive the sound's location, thus indicating the target direction [10]. Evidence has shown that spatialized audio perception is less affected by increased cognitive load on users than language information [10]. In addition, such audio is faster to interpret, more accurate, and more reliable when compared to instructions given in natural language [11].

Haptic stimuli are also used by BVI users for navigation. Adame et al. [12] compared different vibrotactile devices for navigation. Bhatlawande et al. proposed a prototype electronic bracelet whose vibration magnitude is proportional to the distance to an obstacle [13]. K. Moller et al. used the amplitude of vibration to encode velocity information of objects and the vibration time to present the distance to the object [14]. They also proposed that a logarithmic relationship between distance and vibration time is better than a linear relationship, because a logarithmic relationship can be perceived better.

- Headphone

Carrasco et al. found that the BVI are reluctant to wear traditional earphones on both ears while traveling [11], because this can block ambient sound, which the BVI rely on to avoid obstacles [15], [16]. To allow ambient sound to be heard, a solution is to wear open headsets. When only closed headsets are available, then the volume of the audio system should be adjustable to suit the noise level of the environment.

- Ergonomics

Conradie et al. conducted interviews with the BVI and concluded that the BVI generally have fears about the technology failing. They stated, "For a blind person, attempting something as potentially life threatening as crossing the street while relying solely on a technological device may seem daunting." [17] As a result, traditional solutions such as guide dogs, white canes, and care-givers will probably remain their primary assistance. Since one hand of the user is already holding a white cane or a guide dog, the other hand should be set free to protect the user in case they fall. For this reason, the navigation tool we design should not need to be held in the user's hand.

- User-learning

If a user already knows an area by heart, it is much easier for him/her to navigate in this area. However, unlike sighted people who can view traditional maps to acquire this spatial information, the BVI need special tools. The BATS system [18] add spatial sound to position auditory icons and user, while consumer-grade haptic feedback devices provide information through tactile vibrations and textures. Schneider and Strothotte proposed an approach to prepare BVI users with spatial information in a "learning-by-doing" approach [19].

2.3 Indoor positing methods

A variety of indoor positioning systems have been proposed, implemented, evaluated, and even commercialized. These systems can be categorized into three categories based upon the approaches utilized: beacon-based systems, pedestrian dead reckoning (PDR) based systems, and vision-based systems.

In beacon-based systems, the user carries a device, which listens to optical or radio frequency (RF) signals from beacons in the environment. The strength, phase, or time-of-flight of the (Wi-Fi, Bluetooth, infrared) signals is measured and utilized to determine the position of the person. A PDR-based system requires knowledge of the starting position, and then utilizes the orientation and number of steps taken by a person to calculate the next position. A vision-based system captures images from cameras worn by the user, and then analyses these images to recognize the user's position. A typical vision-based product is Easy-living by Microsoft [20].

In this project, we decided to implement a beacon-based system using Bluetooth technology, because today's smartphones are equipped with Bluetooth interfaces and it is easy to access the received signal strength. In contrast, PDR was not considered because the inexpensive sensors implemented in smartphones do not provide very accurate data, which can result in a large accumulated error. Vision analysis was not considered due to its complexity. In a typical vision-based system such as [21], to recognize a location, an image database and location model has to be pre-constructed, which consists of locations and path between locations of an indoor environment. Then, a wearable mobile device captures images and transmits them to a remote server to perform location recognition. The complexity and cost of creating the large image database, the server, and the need for real-time communication between the mobile device and the server are undesirable.

Given that we decided to implement a beacon-based system, the methods used in such systems will be discussed in the following subsections. Of these, the most common methods are fingerprinting and triangulation.

2.3.1 RSSI fingerprint method

One of the simplest methods of doing indoor positioning is to match the RSSI values of signals currently being received from a set of beacons (or other emitters with known locations) with a list of locations with tuples of beacon identifiers and RSSI values. We consider the set of tuples of beacon and RSSI values to be a fingerprint for a location. The assumptions are that such a fingerprint characterizes a single location, that fingerprints are stable over time, that the beacons always transmit at the same emitted power, and that the difference in RSSI values measured at a given location by two different devices have only small differences (less than the differences between the RSSI values at different locations).

2.3.1.1 Mechanism

Technically, a fingerprint is a vector of RSSI values observed at a location. Suppose there are N radio beacons in an indoor environment, where each radio beacon periodically transmits at a fixed transmit power. At time instant t, let $r_i(t)$ be the RSSI value of a signal received from $beacon_i$. Then a fingerprint F can be denoted as:

$$F = [r_0(t), r_1(t), ..., r_{N-1}(t)] \tag{1}$$

The orientation of the user and the smartphone has an impact on the RSSI (due to polarization of the antenna, the user's body absorbing the signal, etc.), hence in some literature (such as [22]) the orientation (indicated as θ) is included in a fingerprint:

$$F = [r_0(t), r_1(t), ..., r_{N-1}(t), \theta] \tag{2}$$

In this thesis, the second definition is used, because we observed that even if a user was standing at a fixed position, the fingerprint value varied significantly with different orientations.

The fingerprinting method has two phases: the offline phase and the online phase.

In the offline phase, fingerprints are collected at certain places to build a radio map. Honkavirta et al. [22] define a radio map as follows:

Suppose we divide the area of interest into M cells and the i_{th} cell is denoted as M_i. The center of such a cell is a reference point p_i (the exact position is measured using a tape measure, laser ranger, etc.). At each reference point, a number of fingerprints are collected, denoted by R_i, with the k_{th} fingerprint being R_i^k. The i_{th} element of a radio map is $M_i = (B_i, R_i)$.

Since each reference point maps to a number of fingerprints, to reduce the memory requirements and computational cost, the radio map can be modified or preprocessed, before applying it in the online phase [22]. In addition, different location estimation methods use different characteristics of fingerprints, such as their mean and variance [22].

During the online phase, a fingerprint at an unknown position is observed and compared to entries in the radio map. The location of the reference point with the "closest fingerprint" (according to some norm) is reported to be the estimated location. The norms to define "closest fingerprint" can be deterministic or probabilistic. These two types of norms are discussed in the following paragraphs.

2.3.1.1.1 Deterministic method

There are a number of deterministic methods [22]. However, here we introduce only the method utilized in this project. This method was chosen due to its simplicity and popularity.

At each reference point, the mean of RSSI values for each access point (AP) or beacon at the i_{th} reference point is calculated, and then this averaged fingerprint is used to represent the reference point. Next, the Euclidean distances between the current fingerprint and averaged fingerprints of all the reference points are calculated using equation (3). The reference point whose fingerprint has the smallest Euclidean distance is the best estimate of the user's location.

$$d(F_i, F_j) = \sum_{k=0}^{N-1} (r_{k,i} - r_{k,j})^2 \tag{3}$$

To help deal with the problems of individual fingerprints, the K reference points with the smallest Euclidean distances are determined. To estimate the actual position of the user, a weighted average of the locations represented by these K nearest reference points is used. This process is the so-called the "K-Nearest-Neighbor" algorithm.

2.3.1.1.2 Probabilistic method

Suppose there are *N* reference points ω_1, ω_2, ... ω_n. The observed fingerprint at an unknown place is S. The location candidate ω_i is chosen if it has the highest posteriori probability $P(S|\omega_i)$. We can compute this conditional probability using Bayes' theorem:

$$P(w_i|S) = \frac{P(S\,|w_i)P(\omega_i)}{P(S)} \tag{4}$$

Since $P(\omega_i)$ remains the same for one positioning process [23], and the prior probability $P(S)$ that a mobile node is located at a specific location is assumed to be the same for all location in the target environment, then the comparison of the posteriori probabilities could be considered a comparison of likelihoods:

Decide ω_i if $P(\omega_i \mid S) > P(S \mid \omega_i)$, for i,j=1,2,3...n, j≠i. (5)

The beacons in the environment are assumed to be independent, so the overall likelihood of one location candidate can be calculated by directly multiplying the likelihood of all beacons.

$$P(S|\,\omega_i) = \prod_{j=1}^{m} P(S_j|\,\omega_i) \tag{6}$$

where m is number of beacons and S_j means the RSS from the j_{th} beacon.

To decide upon the user's position, we can either choose the location candidate with the highest posteriori probability or calculate the weighted average of all coordinates of candidate locations by utilizing their posteriori probabilities as weights.

2.3.1.2 Evaluation

Fingerprinting is a widely used method due to its relatively high accuracy and reliability. Compared to triangulation, where an explicit signal propagation model is required, the fingerprinting method implicitly stores the characteristics of the signal in the radio map, thus complex radio propagation modeling is avoided. A typical indoor positioning system based upon fingerprinting is RADAR developed by Bahl and Padmanabhan at Microsoft Research [24].

However, a severe problem with fingerprinting is its high cost. In the offline phase, much labor and time are required to build the fingerprint database. Moreover, the database has to be updated anytime the environment changes in order to maintain accuracy. To diminish this cost, one solution is to develop efficient and reliable interpolation and approximation methods [25], [26], so that only a few fingerprints need to be collected and additional fingerprints can be predicted (typically by interpolation). Another solution is to implement an organic system that leaves the fingerprint collection to users [27].

In the online phase, matching the observed current fingerprint to a large fingerprint database requires a considerable amount of computation. Sanchez et al. designed a system which uses trilateration to determine a starting point for the search and then applies the fingerprinting to reference points close to this starting point [28].

Considering the fact that many location based services do *not* require an accuracy of 1-2 meters, some researchers propose dividing the indoor environment into cells and then map the user's position to a cell instead of a point[29][30]. In this way, accuracy is traded-off for a dramatic reduction in both online and offline cost.

Besides cost, the accuracy of fingerprinting suffers when there are numerous points (in the training data) with similar fingerprints. This can happen due to factors such as multipath.

2.3.2 RSSI-based triangulation method

Trilateration measures a property of a RF signal (time-of-flight or RSSI), then translates this property into a distance from the device to the beacons (for a location in a plane at least three beacons are necessary), and solves for the position of the device using geometry. In this project, we utilize RSSI to acquire distance information. The following paragraphs describes how to estimate this distance.

2.3.2.1 Mechanism

First, RSSI values from several beacons are measured. Each RSSI value is translated into a distance using a propagation model. A propagation model is an equation that describes the relationship between distance and RSSI. Equation (7) is a standard indoor path loss function which requires knowledge of a number of variables in order to determine the path loss, where L denotes the indoor path loss and the unit is in decibels (dB) and N denotes the distance power loss coefficient (in dB) which can be obtained from Table 2-1.

$$L = 20\log_{10}(f) + N\log_{10}(d) + L_f(n) - 28 \tag{7}$$

Table 2-1: **Distance power loss coefficients (in dB) [31]**

Residential	Office	Commercial
28	30	22

For example, when N = 30 and f = 2.4GHz (the frequency of Bluetooth's signals), the equation can be simplified to

$$d = 10^{\frac{L-39.6}{30}} \tag{8}$$

Three circles can be drawn with the center of each circle being the position of the corresponding beacon and the radius being the distance. In the ideal case, all of these circles intersect at one point as shown in Figure 2-1. This point is the estimated position of the receiver.

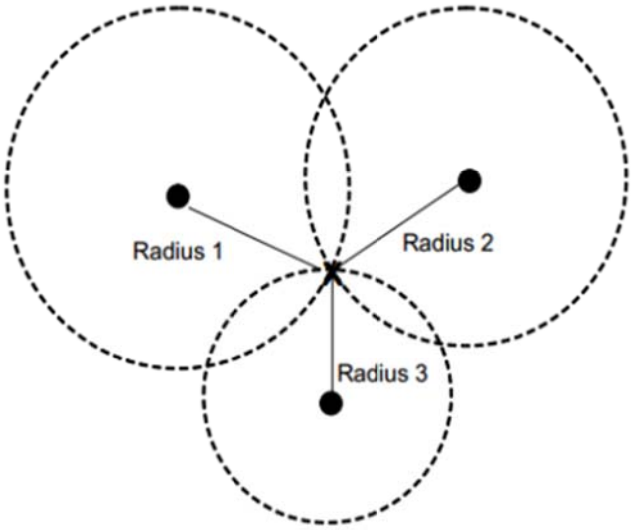

Figure 2-1: **An example of trilateration**

As mentioned earlier, time-of-flight can be utilized to calculate the distance from the device to the beacons. One method to determine these distances is by measuring the time of flight of a signal (such as a radio or acoustic signal) and multiplying it with the propagation velocity of the signal in the media [32]. Time-of-Arrival (TOA) and Time-Difference-of-Arrival are two widely used methods based on time measurements. However, these methods are not used in this project, because today's smartphones do not provide timestamps with a sufficient resolution, which leads to a large distance error. In 2014, Jacob Philips et al. [33] used a simple TOA algorithm to measure the distance between two Nexus 4 Android smartphones using Bluetooth and two different timestamp sources. The result shows that even the best distance estimates were on the order of 10^6 meters while the actual distances were between 0 and 8 meters. They concluded that the smartphones today are not able to measure accurate TOA distances without assistance from smartphone hardware vendors.

2.3.2.2 Evaluation

Yang and Liu noted the following challenges for the trilateration method [34]. These phenomena were also observed in our experiments.

1. **Uncertainty**: Due to factors such as multipath fading, reflection, the three circles used in trilateration often do not intersect at a common point, as shown in Figure 2-2. Thus, there is no single point which meets all the distance constrains.

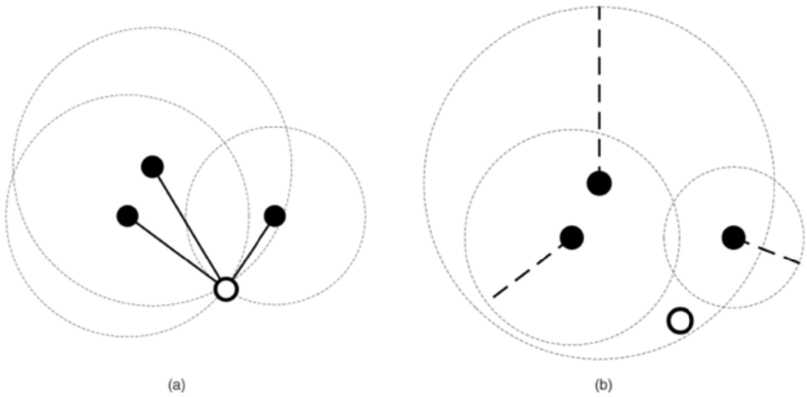

Figure 2-2: An example of uncertainty in trilateration (Adapted from [34])

2. **Nonconsistency**: When there are more than three available beacons, each subgroup of three beacons is able to give a trilateration result. These results often vary and it is difficult to determine which result is the most accurate.

   Beacon selection is applied to solve this problem. A traditional way is to select the strongest three beacons. Chen et al. introduces an intelligent beacon selection algorithm that requires offline training [35].

3. **Propagation model error**: A propagation model is needed that describes the RSSI-distance relationship that applies to the actual propagation environment. We need this propagation model to translate the RSSI value to a distance. Various models have been proposed by researchers, such as: empirical models, deterministic models, and semi-empirical models. Some researchers use an offline phase to collect RSSI values at reference points to calculate a local propagation model . Other approaches utilize mutual measurements between access points [36], or they use sniffers to dynamically estimate the propagation model [37]. Mazuelas et al. [38] propose a novel method that does not required any calibration stage, map information, or making changes to the wireless network. They utilize only RSS measurements obtained in real-time and use a pure software solution to estimate the propagation model.

2.3.3 Kalman filter

Filters can significantly improve the positioning results in comparison with static methods. The Kalman filter is a data fusion algorithm for linear systems. Such a filter can be used to smooth noisy data and estimates of unknown variables. This type of filter is popular because of its low computational requirement. One of its famous application was in the Apollo navigation computer that took Neil Armstrong to the moon, and (most importantly) brought him back [39]. Nowadays it is widely used in signal processing.

There are two important equations in the filtering process.

$$z_t = H_t X_t + v_t \tag{9}$$

$$X_t = F_t X_{t-1} + B_t u_t + w_t \tag{10}$$

X_t is the true state at time instant t and z_t is the measurement of the state at time instant t.

Equation (9) indicates that the measurement z_t is different from the true state of the system X_t due to the existence of noise v_t. A transition matrix H_t is applied when the measurement and the state are in different domains. For example, traveling time is measured in unit of seconds, while the state is a distance or position in meters. The noise v_t is assumed to have a Gaussian distribution, thus the measurement z_t also has a Gaussian distribution.

Equation (10) predicts the true state X_t, by combining the last state X_{t-1}, the control input u_t and the noise distribution w_t.The matrices F_t and B_t are transition matrices that can be deducted from the model of system. For example, in the case of a vehicle moving at a constant velocity, u_t will be the known constant velocity, while F_t and B_t represent Newton's law of motion.

Using equation (9) and (10), we obtain two Gaussian distributions that can be used to estimate the true state: one from the measurement and one from the prediction. To obtain the final best estimate, we multiply the probability density function (PDF) of these two Gaussian distributions, which results in a new Gaussian distribution, as shown in Figure 2-3. The mean value of the new Gaussian distribution has the highest probability density; thus, it is the best estimation result.

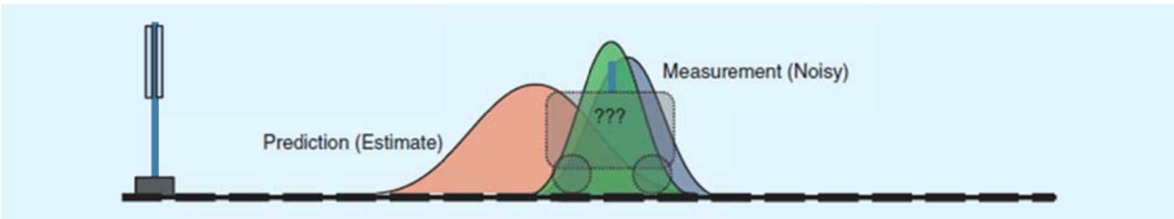

Figure 2-3: Using the Gaussian distributions to estimate the true state[39]

Figure 2-3 shows the new PDF (green) generated by multiplying the PDFs associated with the prediction and measurement of a train's location at time instant t. This new PDF provides the best estimate of the location of the train, by fusing the data from the prediction and the measurement.[39] This result will be used as X_{t-1} in the next epoch to produce the next estimate. As we can see the Kalman filter works recursively.

2.3.4 Clustering

Dividing the area of interest into clusters helps to greatly reduce the computational cost. The idea of clustering is that locations where the received signals have similar characteristics form a cluster (in a feature space). We begin by identifying a cluster to which an unknown sample belongs, and then further determine an approximate position within the cluster.

2.3.5 Post-processing of positioning results

While triangulation and fingerprinting provides static localization, a navigation system is actually a dynamic tracking system, where users are assumed to move continuously. This means that positions during a sequence of time are actually correlated. This correlation can be exploited to achieve better accuracy.

There are motion constraints and geographical constraints that can be applied to dynamic tracking in indoor environments. These constraints can be used to avoid logical errors, such as the user "flying" 5 meters in one second, or generating a localization result indicating that the user is actually on a desk or a bookshelf*. By dividing the map into cells, the movements of the user correspond to finite states. If we assume that the current states only depend on the previous state, then we can model the movements as a Markov chain.

2.3.6 Markov Localization

A Markov chain describes a random process that undergoes transitions from one state to another in a state space. A Markov chain consists of states and transition probabilities between states. Figure 2-4 show a simple Markov chain with only three states: A, B, and C.

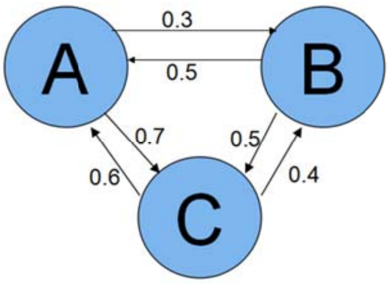

Figure 2-4: Example of a simple 3-state Markov chain

In the positioning scenario, a state is a position where the user can be. If we divide the indoor environments into cells, then the system has finite states (corresponding to the cells). We assume that initially a user can be in any cell (the probability of being at any place has a uniform distribution model). For the transition probability matrix, we apply a simple heuristic, i.e., the walking speed of people does not exceed 3 meters per second. As a result, knowing the current position, we are able to calculate where the user probably is during the next epoch.

2.4 Related work

We consider two categories of related work:

- The first category are indoor positioning systems that utilize RSSI (either Wi-Fi or Bluetooth) to determine positions and run on smartphones. We study these for the methods used as inspiration and subsequently for comparison with their performance. However, such systems do not necessarily have a user interface (UI) for BVI users.
- The second category consists of positioning systems specifially targeting BVI users. These systems do not utilize RSSI to determine positions, so they are not technically similar to our project; however, their performance and UI design are of interest.

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* Of course, since we are actually tracking the smartphone – it could have been thrown, placed on a desk or bookshelf, etc. However, as this thesis focuses on BVI users we will assume that the smartphone moves with the user.

2.4.1 Indoor Positioning systems utilizing RSSI and running on smart phones

The indoor positioning systems shown in Table 2-2 utilize RSSI to determine positions. They either use fingerprinting or triangulation. Some systems combine RSSI-based methods with other methods such as PDR and camera scene analysis. These systems also run on smartphones, so it is good to compare their performance with our system's performance.

Note that most of the systems utilize Wi-Fi signals, but those that utilize Bluetooth signals are marked with ***.

Table 2-2: Analysis of similar systems

Authors	Technique/Algorithm	Accuracy
Wang et al. [40]***	Triangulation with least-square-estimation, three-border and centroid method	Not available
Grzechca et al. [41]	Kalman filter	6.409m
Kim et al. [42]	Cross monitoring AP, least-squared-error triangulation	<2m
Gutierrez et al. [43]	Classify RSSI using clustering and Naive-Bayes algorithm	80%
Ji et al. [44]	Autonomously and dynamically generating fingerprint databases	2.62m
Huang et al. [45]	Crowd-based fingerprints collecting approach	1.3m
Li et al. [46]	Fuses RSSI and inertial sensor measurements	Reduces error by 65% compared to not using inertial sensors
Uddin et al. [47]	Fuses RSSI, acoustic sound and inertial sensors	Less than 1 m accuracy for more than 90% of the time
Kim et al. [48]	Peak-based fingerprinting, k-NN, PDR and particle filter	Not available
Agrawal et al. [49]	Camera and fingerprinting	1-1.5 m
Gani et al. [50]	Fingerprinting and inertial sensors	Less than 2.5m

2.4.2 Positioning systems designed for the BVI

In this subsection, we discuss those positioning systems that target BVI users.

Apostolopoulos et al. designed an indoor positioning system running on a smartphone utilizing only the inexpensive sensors equipped in the phone [51].

Zeb, Ullah, and Rabbi designed and implemented an indoor auditory navigation system for BVI [52]. This system utilizes cameras and is based upon scene analysis. This system works in two modes: free mode where the user walks freely and he/she will be informed of his/her position; and targeted mode where the user is guided from a source position to his/her desired destination.

There are audio guidance systems for the BVI which are already in the market, such as Sendero Group's The Seeing Eye GPS [53] and Kapsys' Kapten Mobility [54]. Both of these systems are designed for outdoor environments.

2.5 Summary

Table 2-3 gives a summary of the positioning techniques described above. The advantages and disadvantages motivated my decision to implement a system based upon electromagnetic waves.

Table 2-3: Comparison of existing indoor positioning techniques

Systems	Measurement	Advantage	Disadvantage
Electromagnetic systems	RSSI/ time/phase of waves	Simple and accurate	Only available in places with beacons deployed
Pedestrian dead reckoning	Orientation and step length of users	Minimum infrastructure required, available in any environment	Low accuracy when utilizing sensor in smartphones
Vision based	Images captured by wearable cameras	High accuracy	High complexity

There are several ranging techniques used in systems based upon electromagnetic waves. Table 2-4 summarizes these ranging techniques. The advantages and disadvantages motivated my decision to use a ranging technique based on RSSI measurements.

Table 2-4: Comparison of ranging techniques

Category	Principle	Technique	Detail	Are required data from a smartphone reliable
Trilateration	Determine a position by the intersection of three circles	RSSI-based	Measure RSSI and translate it to distance	Yes
		TOA/TDOA(time difference of arrival)	Measure time-of-flight and translate it to distance	No
Triangulation	Determine a position by two angles	AOA()	Measure angles of arrival of a wave	No

3 Methodology

The purpose of this chapter is to provide an overview of the research method used in this thesis. First, we explain the research process. Then we describe the research paradigm, data collection techniques, and experimental design. Section 3.5 explains the techniques used to evaluate the reliability and validity of the data collected. Section 3.6 describes the method used for the data analysis. Finally, Section 3.7 describes the framework selected to evaluate the performance.

3.1 Research Process

Figure 3-1 shows the steps conducted in order to carry out this research.

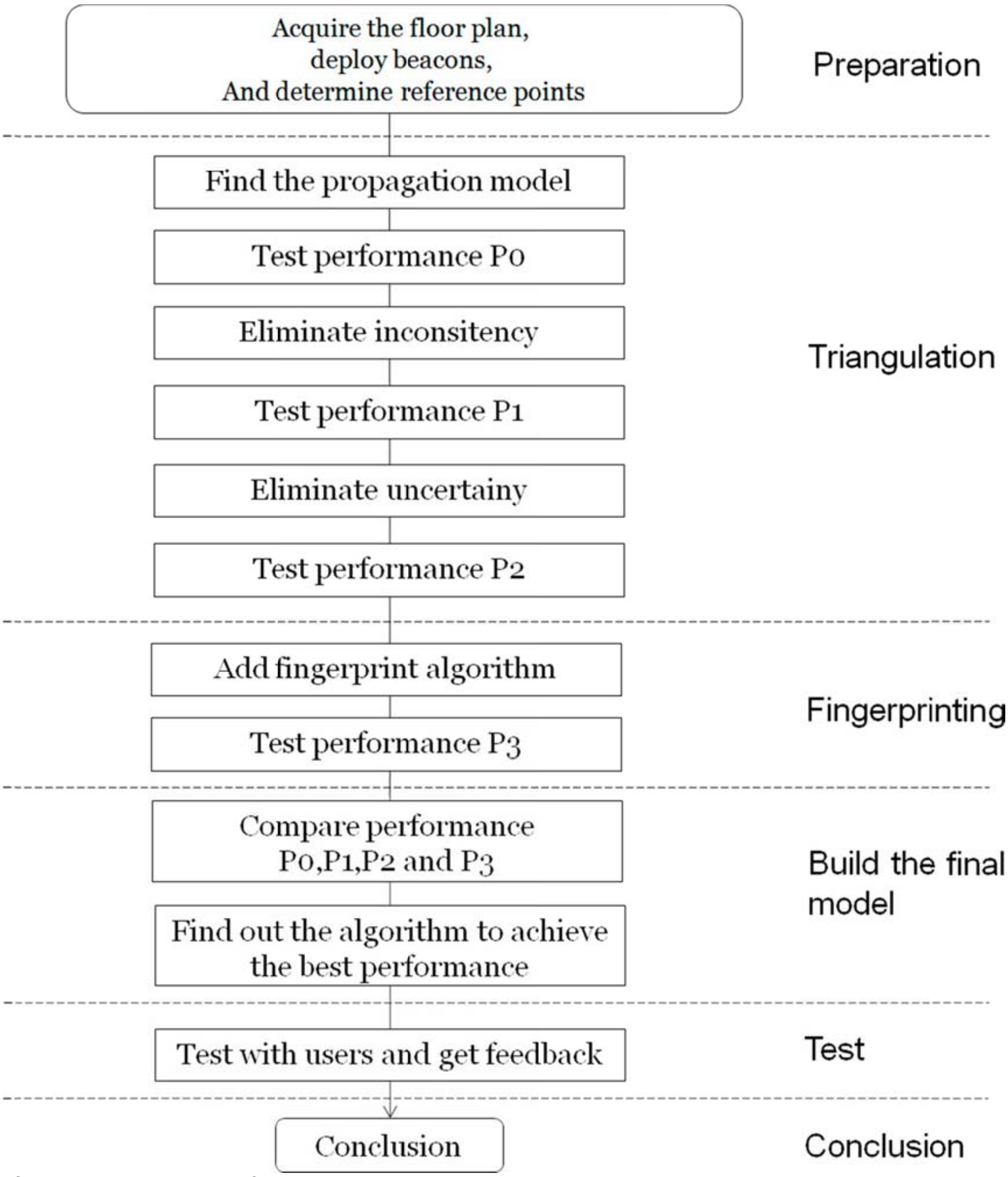


Figure 3-1: Research Process

3.2 Research Paradigm

When researching the quantitative performance (accuracy, precision, etc.) of indoor positioning systems, we adopt a realism paradigm - because the performance of the system does *not* depend on the observer. We collect data from experiments and develop knowledge from this data.

In contrast, when evaluating the UI of the indoor positioning system, we adopt a interpretivism paradigm - because our aim is to understand users' opinions and to conclude desirable characteristics of this UI from their opinions.

3.3 Data Collection

To evaluate the quantitative performance of the system, we collect data from experiments. To evaluate the UI, we perform interviews and collect user' opinions.

3.3.1 Sampling

To measure the performance of this system, we choose 25 references points on a map, as shown in Figure 3-2. There are 12 points in the corridor, with the distance between each point being approximately 1 meter. There are 13 reference points in different rooms and these positions are distributed over these rooms.

The density of reference points is much higher in the corridor than in the rooms. The reason for this choice is that in a real user case, people's destination is often a specific room, rather than a specific position inside a room. Thus, when evaluating the system, the positioning performance in the corridor should have a higher weight.

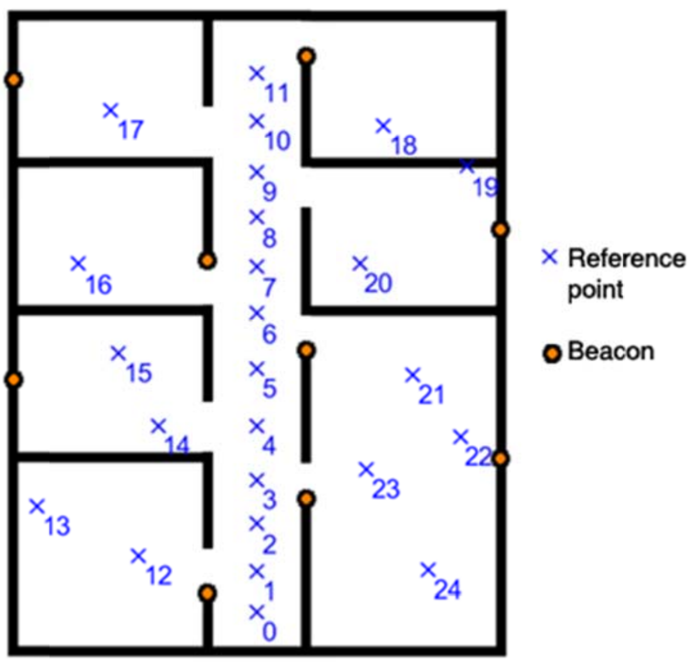


Figure 3-2: Distribution of reference points for performance measurement

3.3.2 Sample Size

When measuring the performance of the system, a person will stand at each reference point for 10 seconds to collect 10 samples of RSSI values for each beacon of interest at this location. Thus, the sample size for each of these 25 reference points is 10.

3.3.3 Target Population

The target population is BVI users.

3.4 Experimental design/Planned Measurements

This section describes the test environment and the hardware and software that were used for the experiments.

3.4.1 Test environment/test bed/model

We collected data and our system in two environments.

Environment A is an indoor space that consists of 8 rooms and a corridor, as shown in Figure 3-3. The dimensions of this space are 1000 cm * 1296 cm. The numbers 401-408 are room numbers. There was no furniture or people inside this space. Such kind of space is not very representative of the space that BVI need to navigate. However, by doing experiment in such environment helps us understand the upper limit of the system performance, because having more furniture and people inside the environment will hinder the line-of-sight propagation, result in more reflection, thus probably downgrade the performance.

Environment B (shown in Figure 3-4) consists an open space on the ground floor, an elevator, and an office space on the 4th floor.

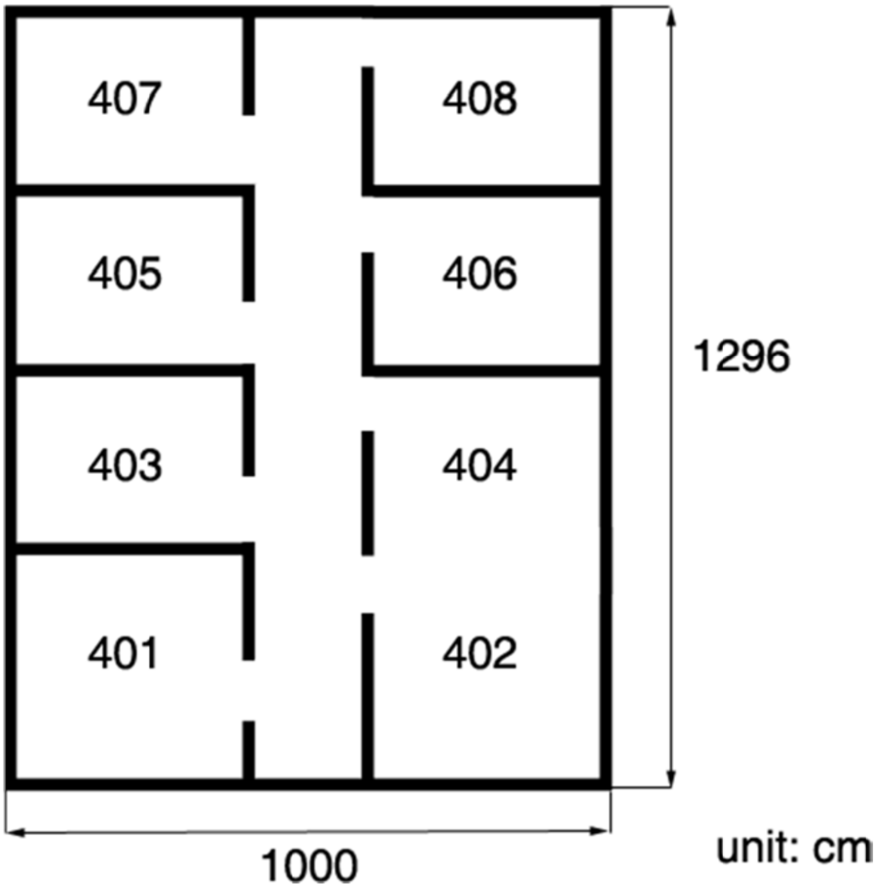


Figure 3-3: **Test environment for static positioning result**

Figure 3-4: **Test environment for navigation**

3.4.2 Hardware/Software to be used

A Google Nexus 5 phone was used to collect RSSI signatures, calculate a position, and present this information to the user. Sweden Connectivity AB developed and produced the Bluetooth beacons that were used in the experiments. Each Bluetooth beacons use 4 AA battery for power. These batteries provide power for 2-3 years.

3.5 Assessing reliability and validity of the data collected

This section describes how I will test the reliability and validity of the data that is collected.

3.5.1 Reliability

We will perform identical experiments at least 3 times and check if the results of these experiments are consistent and stable. We repeat these experiments until the observed results have a reasonable and acceptable variation. We define “acceptable variation” as: If the average of all the results is x, then all the results should fall in the range [0.9x, 1.1x].

3.5.2 Validity

There are three variables directly measured in this project: users’ true positions, users’ positions estimated by the system, and navigation time. These three variables were measured as follows:

- The true position of the user is measured by a 2-meter ruler with a minimum scale of 1 mm. We utilized a second ruler to test if the ruler being used gives correct measurements.
- The navigation time is measured by the smartphone Nexus 5. We used the timer in another mobile phone, an iPhone 6 to test if the timer in the Nexus 5 was accurate.
- The estimated position is calculated by software in the smartphone. To guarantee there is no bug in the software causing any error, we tested the correctness of the software by inputting dummy RSSI data to a test script and verify the results by comparing the positioning result from the app and the positioning result from the test script.

3.6 Planned Data Analysis

The following subsections describe the techniques and software I chose for data analysis.

3.6.1 Data Analysis Technique

To evaluate the quantitative performance of the system, we calculate statistics and significance of the results. To evaluate users’ attitudes and perspectives regarding the system, we employed coding of transcriptions of interviews.

3.6.2 Software Tools

Mathworks’ Matlab R2014b was used to process all of the data. This software generated all of the data analysis figures.

3.7 Evaluation framework

The following subsections describe each of the metrics I chose to evaluate the positioning system.

3.7.1 Accuracy

Accuracy is usually defined as the mean distance error, which is the average Euclidean distance between the estimated location and the true location[55].

Definition. Suppose there are N positioning attempts. Let $P_{real,i}$ be the true position and $\hat{P}_i$ be the estimated position at the i_{th} attempt, then accuracy (ε) can be denoted as:

$$\varepsilon = \frac{1}{N}\sum_{i=0}^{N-1}\left\| P_{real,i} - \hat{P}_i \right\| \tag{11}$$

3.7.2 Precision

Accuracy considers only the mean distance error, hence another metric is needed to reveal the variation in the positioning errors over many trials, this metric is precision.

There are several definitions of precision. In some litature, precision is defined by the cumulative distribution function (CDF) of the overall positioning error. In other literature, precision is defined by the standard deviation in the location error or the geometric dilution of the precision. Although there are several different definitions, they all give a general picture of the variation of the positioning error. In this thesis, we use the second definition: precision is the standard deviation in the location error. We use this definition because of its simplicity.

3.7.3 Failure rate to determine a position

The system tries to calculate the user's position every 1 second. However, at some moments, the system fails to determine the position. The reason is that triangulation uses the intersection of circles to determine a position. Thus, in the case that none of the circles intersect, the system is not able to determine the user's position. As described in Section 3.3.2, in one experiment of evaluating the system's performance, we collect 10 positioning results for each of the 25 reference points. In total, the system tries to determine the position 250 times. The failure rate of determining a position can be defined as the percentage of failures over the 250 samples:

$$\mathrm{F} = \mathrm{f}/250 \times 100\%$$

F denotes the failure rate (in percent), while f denotes the times that the system failed to determine a position.

3.7.4 Navigation time

Measuring accuracy and precision requires that we know the user's true position. While this position is available for static positions, where the user stands still; this is not the case for dynamic tracking as the user may be continuously moving. For this purpose, we propose another metric to benchmark the system's navigation performance. The metric that is proposed is the time needed for the user to navigate to their final destination from a starting point. If the system fails to navigate the user to the correct position, then the navigation time is set to infinity.

3.7.5 Cost

In a fingerprinting technique, the offline phase of measurements builds a database of fingerprints. Generally, the larger this database is, the better the accuracy that can be achieved. However, this results in a larger cost at run-time and greater human effort required to collect these measurements. In this thesis project, cost is computed as the number of fingerprints required per square meter of the environment.

Definition: If M fingerprints are taken within a surface area of S square meters, then the fingerprint cost is defined as:

$$C_{fingerprint} = \frac{M}{S} \tag{12}$$

3.7.6 Complexity

In the literature, complexity is introduced as another metric to use when benchmarking a system. Complexity can be measured in terms of the time required to calculate the position of a device. However, current smartphones have sufficient processing capacity that when using the algorithm used in this thesis, that the computation time is less than 0.1 seconds; thus, time consumption is not a major factor in our assessment of this method. Therefore, this metric was not used in this project.

3.7.7 BVI user's mobility, independence, and autonomy

Since the target users of this system are BVI, it is relevant to evaluate whether this system results in better mobility, independence, and autonomy for these users. The method used in this thesis project to evaluate these metrics is to test the system with BVI users and interview them

.

4 Implementation of the positioning systems

In this chapter, first we show the architecture of the software in order to give a general overview of the system. Next, we explain in detail our design decisions when implementing the positioning functionality. Finally, we explained our design decisions for the navigation system.

4.1 Software design

The software is realized as an Android application with six layers (see Figure 4-1). The first four layers implement a static positioning system. The last two layers enable the system to be used as a navigation system.

The first layer consists of two services: the RSSI service and the orientation service. These services start immediately when the application starts and continue running until the application is terminated. The RSSI services listens to all the Bluetooth signals in the environment and reports the RSSI values of these signals and the MAC address of the corresponding beacon. The orientation service reports the orientation of the mobile phone.

The second layer is a pre-processing layer. In this layer, the RSSI values of the beacons of interest (their MAC addresses are hardcoded in the software)are sampled every 0.1 second. After one second, 10 samples should be collected. Of these 10 samples, null values and abnormal spikes (RSSI values that are stronger than -10 dB) are discarded, while the remaining values are averaged and reported to the third layer.

The third layer is the core of the system, i.e., the positioning algorithms. In this thesis, we implemented triangulation, fingerprinting, and a proximity algorithm. The details of these algorithms are given in the following subsections. The user's current position is calculated in this layer.

The fourth layer draws the user's position on a map. This functionality is only for presentation purposes, as it is not relevant for BVI users.

The fifth layer compares the users' position and orientation to their designated route, and generates navigation instructions for BVI users based on this information. The sixth layer plays these navigation instruction and vibrates the phone.

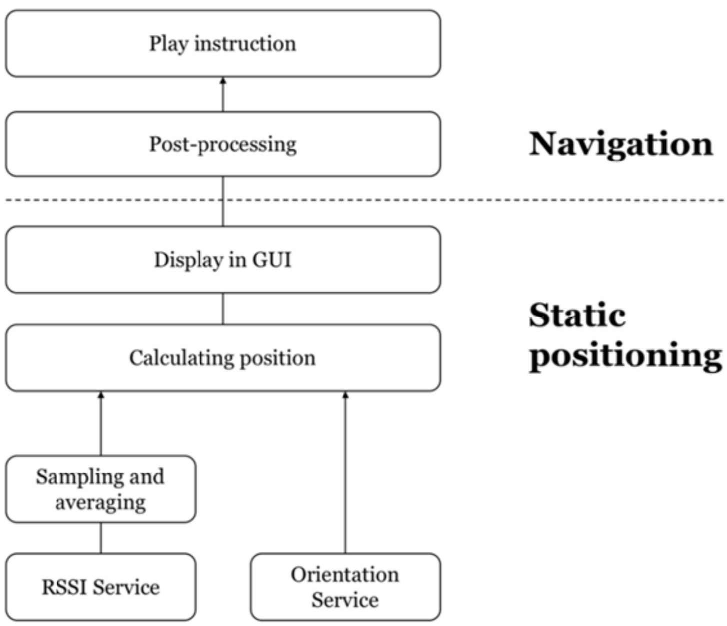


Figure 4-1: The architecture of the software

4.2 Implementation

In the chapter, we describe in the detail about our design decisions for the algorithms and user interface, and how we implemented them. We also explained how we designed the experiments and results of these experiments.

4.2.1 Triangulation

As aforementioned in Section 2.3.2.2, when using triangulation in a real environment there are three problems to solve: creating a propagation model, eliminating inconsistency, and eliminating uncertainty. Below we will explain how we implemented our system to solve these three problems.

4.2.1.1 Find the propagation model in the specific environment

According to Zhe Xiang at al. [56], a propagation mode is very environment-specific and antenna-specific. Therefore, it is impossible to find one equation that suits in all conditions. Thus, we propose a method to empirically measure an environment and create a propagation model for this specific environment.

First, we collect RSSI values at different locations within this environment. Then, we conduct regression analysis using general propagation models.

To build the propagation model we conducted an experiment as described in the following paragraphs.

We deploy one beacon on a wall. The height of the device is the same as the height of the beacon. We stood at different locations(randomly chosen) and collected 300 samples at each location. We use an average of these 300 samples at each position to represent the real value in this position. Table 4-1 shows the data that was collected.

Table 4-1: RSSI values at different distances from a beacon

Distance (m)	1.00	1.11	1.41	1.80	2.23	2.69	3.16
RSSI (dB)	-48.1	-52.5	-53.1	-61.4	-60.9	-61.9	-70.3

After collecting data, we use Matlab to perform a regression analysis of this data. The general equation we are using is $RSSI = a \times 10^{bx+c}$ which is similar to equation (7). Here x denotes the distance in meters and RSSI is in units of dB. Figure 4-2 shows the curve fit to these measurements.

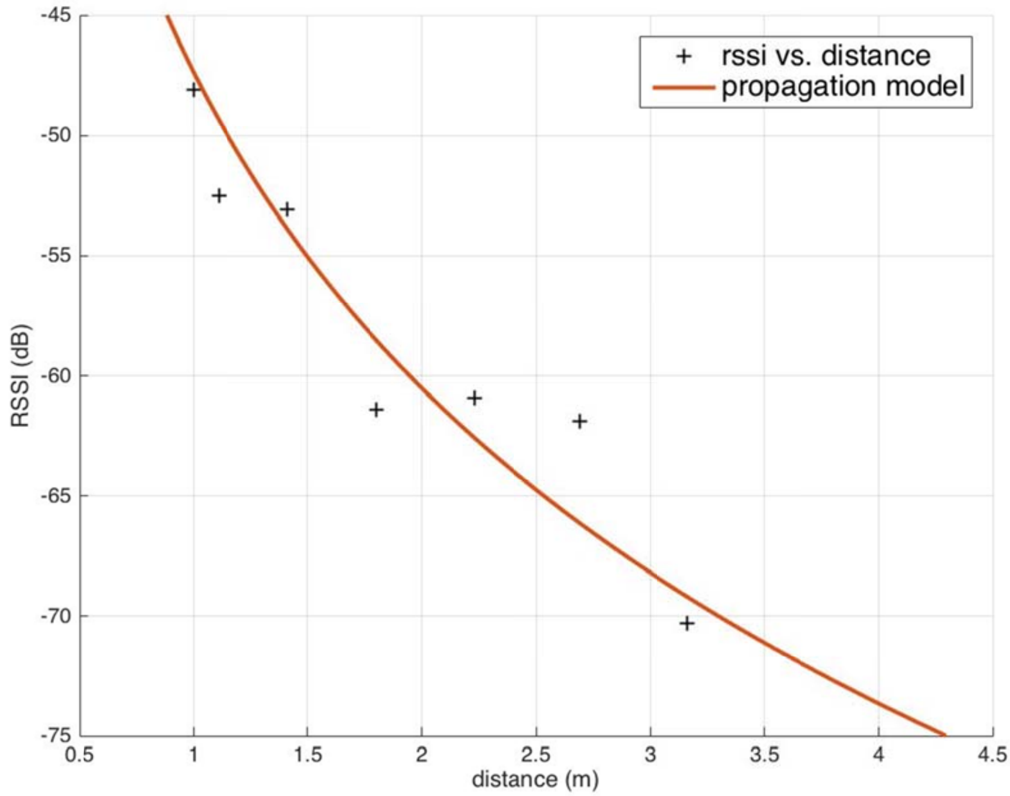


Figure 4-2: **The regression analysis for propagation model**

The regression analysis gives a best fit when a = 1.448, b= -0.02291, and c = -1.246. The goodness of fit by SSE (The sum of squares due to error) is 0.5136, by R-square is 0.8716. The relationship between RSSI and distance is:

$$RSSI = 1.448 \cdot 10^{-0.02291x-1.246}$$

Thus, the propagation model we have is

$$distance = \frac{log_{10}\left(\frac{RSSI}{1.448}\right) + 1.246}{-0.02291}$$

Now that we have a propagation model, we test the system's performance. We use all nine beacons to determine a position. These nine beacons form nine circles. Suppose there are N intersetions of the nine circles, and the i_{th} intesection has coordiantes (x_i, y_i). Suppose x_m is the medial value of all the x coordiantes(x_o to x_{N-1}), and y_m is the medial value of all the y coordiantes(y_o to y_{N-1}). We use the position (x_m, y_m) as the user's position.

Figure 3.3 showed the locations where we tested the performance. Section 3.3.2 described the steps to test the performance. Table 4-2 shows the performance of this system.

Table 4-2: Positioning results of triangulation

	Accuracy (cm)	Precision (cm)	Failure rate to determine position (%)
Experiment 1	416.2	104.8	0
Experiment 2	423.5	99.6	0
Experiment 3	433.4	96.7	0
Average	424.4	100.4	0

This performance is unsatisfactory. I decide to solve the problem of uncertainty and inconsistency, and see if it will improve the performance . In the following subsections we discuss changes to our design to reduce uncertainty and achieve greater consistency, and then show how these changes improve the accuracy.

4.2.1.2 Eliminating inconsistency: selecting a subset of beacons

Triangulation requires at least three circles to determine a position. In the last experiment, we used all nine beacons. However, since the signal strength from a beacon is not stable due to reflection and multipath effect, we wonder if using more beacons will contribute to a better accuracy, or actually introduce more errors to the result.

Thus, we did another experiment. In this experiment, we consider only the three strongest beacons when calculating a position, instead of considering all nine beacons. Table 4-3 shows the system's performance.

Table 4-3: Positioning result with triangulation and beacon selection

	Accuracy (cm)	Precision (cm)	Failure rate to determine position
Experiment 1	245.0	117.7	56%
Experiment 2	278.7	141.6	44%
Experiment 3	282.3	158.6	43%
Average	268.7	139.3	48%

We can see that, comparing to experiments using all nine beacons, using the three strongest beacons dramatically improved accuracy by 155.7 centimeters. However, the drawback is that the failure rate to determine position increased from 0 to 48%. By observation, we realized that this problem arises because in many cases, the chosen 3 beacons do not intersect at all, thus we fail to determine a position. We will discuss how we solved this problem as follows.

4.2.1.3 Eliminating uncertainty

To solve the problem with non-intersecting circle above, we proposed a way to calculate a "pseudo-intersection" when circles do not intersect. We do this because ideally all the circles should intersection at one point, as is shown in Figure 4-3(a). However, in most cases there are multiple intersections, which leads to uncertainty.

To eliminate this uncertainty, we use the medial or an average value of all intersection coordinates to reduce the impact of outliers, i.e., points that are extremely distant from other points.

(a) ideal case: one intersection (b) multiple intersections

Figure 4-3: Using medial coordinate to eliminate uncertainty

When applying this strategy, we noticed there is another phenomenon which results in large errors. This occurs when some beacons are very strong, thus the distance between the user and beacon is small, the range of the circle is also so small that it does not intersect with other circles. Since there are no intersections, a very strong beacon does not contribute any information to the positioning result, as it is as if this beacon does not exist. This is undesirable because a strong beacon is usually more reliable.

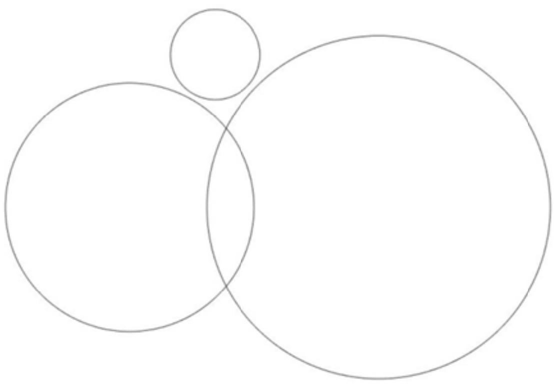


Figure 4-4: The case when one signal is too strong that its circle does not intersect with other circles

Thus, we propose the second strategy to eliminate uncertainty. Even if the circles do not intersect, we calculate a "pseudo-intersection" as follow:

Circle A(B,C) has its center at point A(B,C), with a radius of $r_A(r_B, r_C)$.

1. Draw a line that links point A and point B. This line intersects circle A at point (x_A, y_A), and intersects circle B at point (x_B, y_B).

2. Calculate the weights of the two circles.

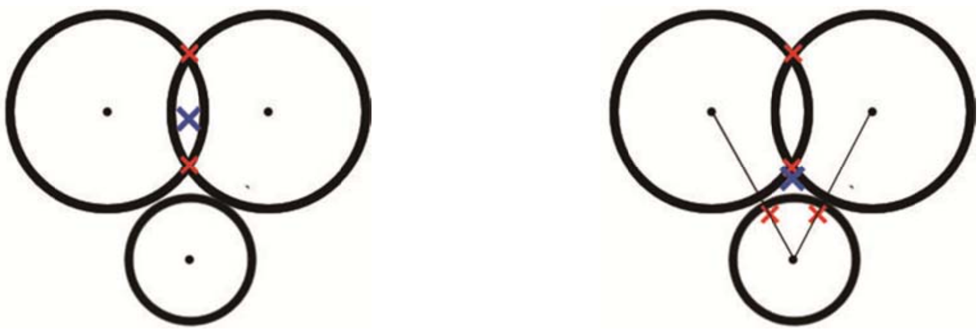
$$w_A = \frac{r_A}{r_A + r_B} \qquad w_B = \frac{r_B}{r_A + r_B}$$

3. Pseudo-intersection's coordinates:

$$x = x_A \cdot w_A + x_B \cdot w_B \qquad y = y_A \cdot w_A + y_B \cdot w_B$$

From this calculation, we see that a pseudo-intersection is a point on the line that links the centers of two circles, and the exact position is a weighted average of the two intersections of the line and the circles.

Figure 4-5 illustrates the difference between using and not using pseudo intersections. In Figure 4-5 (a), since the smallest circle does not intersect with the other two circles, we only have two intersections. The medial point of the two points (indicated by the red "x" on the lines) is used as the positioning result. In the case shown in In Figure 4-5(b), we calculate one pseudo-intersection for circle AC (BC), thus we have four intersections. We use the median point of all four intersections as the positioning result (the blue cross) We can see that when using the pseudo-intersectionz, the positioning result moves closer to circle C.



(a) (b)

Figure 4-5: **Pseudo intersection**

We assume that using the pseudo-intersections will improve accuracy, because it does not exclude beacons that do not have actual intersections. To prove this, we did an experiment. We use the propagation model calculated earlier and we always choose the strongest three beacons. However, we compare the use and non-use of pseudo-intersections. Each experiment was repeated three times so that we can test reliability of the results.

Table 4-4: **Using all nine beacons and using pseudo intersection**

	Accuracy (cm)	Precision (cm)	Failure rate to determine position
Experiment 1	331.9	45.8	0%
Experiment 2	332.3	54.1	0%
Experiment 3	336.8	49.6	0%
Average	333.7	49.8	0%

Table 4-5: Using 3 strongest beacon and using pseudo-intersection

	Accuracy (cm)	Precision (cm)	Failure rate to determine position
Experiment 1	180.2	128.9	0%
Experiment 2	205.9	120.6	0%
Experiment 3	213.3	133.6	0%
Average	199.8	127.7	0%

The result shows that either using all nine beacons or using the strongest three beacons and using pseudo-intersections, greatly improves performance.

If we compare the results in Table 4-3 and 4-5, we find that using three strongest beacons and applying pseudo-intersections, reduces the failure rate from 48% to 0% and increased accuracy by 68.9 centimeters and improved precision by 11.6 centimeters.

4.2.2 Fingerprinting

The best results from the previous section showed an accuracy of 199.8 cm, precision of 127.7 cm, and 0% failure to determine position – when using only the triangulation algorithm. Therefore, we examine if adding fingerprinting to the triangulation algorithm improves performance. The idea is that combining both triangulation and the fingerprint algorithms will improve both accuracy and precision – but selecting the appropriate method at each position.

We examined fingerprinting's reliability by calculating a "fingerprint error", i.e. the Euclidean distance between the current fingerprint and best-matched fingerprint in the database. When the fingerprint error is smaller than some threshold, then we consider the fingerprinting result as reliable and use it as the position. Otherwise, we use the triangulation result as the position.

Another design decision concerning fingerprinting is that we utilize fingerprints only when the accuracy is lower than average, rather than taking fingerprints everywhere in the environment. This is essential because taking fingerprints everywhere costs a lot of labor and time. In order to evaluate this we examined the raw data and identified those places where the accuracy was lower than average. The results are shown in Table 4-6, while Figure4.6 shows where these points are located in the environment.

Table 4-6: Places with accuracy lower than the average

Point index	24	13	0	18	19
Accuracy (cm)	419.2	348.8	344.4	312.4	287.8
Point index	14	22	12	15	20
Accuracy (cm)	259.2	242.4	240.1	219.9	215.5

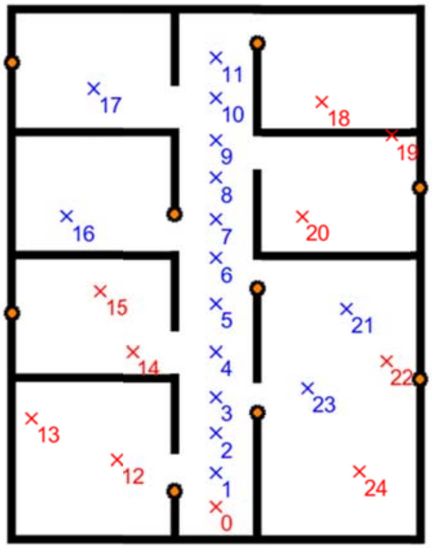


Figure 4-6: Places where the accuracy is lower than average

We decide to use the K-Nearest-Neighbor (KNN) algorithm for fingerprinting. As the fingerprints are very sparse, we believe that selecting more than one "neighbor" in the KKN algorithm probably will result in an even worse performance. For this reason, we tested the performance starting with K =1 using three experiments, with the threshold being 4, 5, and 6. These results are shown in Table 4-7, Table 4-8, and Table 4-9

Table 4-7: Performance with Fingerprint Error Threshold =4, KNN K=1

	Accuracy (cm)	Precision (cm)	Units?
Experiment 1	197.6	146.2	0
Experiment 2	203.9	142.3	0
Experiment 3	211.8	161.4	0
Average	204.3	150.0	0

Table 4-8: Performance with Fingerprint Error Threshold =5, KNN K=1

	Accuracy (cm)	Precision (cm)	Null position
Experiment 1	173.2	140.2	0
Experiment 2	190.2	150.4	0
Experiment 3	185.5	164.2	0
Average	182.9	151.6	0

Table 4-9: Performance with Fingerprint Error Threshold =5, KNN K=1

	Accuracy (cm)	Precision (cm)	Failure rate to determine position
Experiment 1	214.7	205.1	0%
Experiment 2	212.4	201.7	0%
Experiment 3	219.4	190.9	0%
Average	215.5	199.2	0%

From the above result, we came to the conclusion that when the K equals 1 and the Fingerprint Error Threshold is 5, then the system achieves its best performance. To confirm this, we did another experiment with K =2. Table 4-6 shows the results. As we expected, when fingerprints are sparse, utilizing more than one reference points degrades the performance.

Table 4-10: Performance with Fingerprint Error Threshold =5, KNN K=2

	Accuracy (cm)	Precision (cm)	Failure rate to determine position
Experiment 1	214.7	163.0	0%
Experiment 2	215.8	153.5	0%
Experiment 3	213.6	160.6	0%
Average	214.7	159.0	0%

We draw the conclusion that fingerprinting improves the performance of the system. Additionally, the configuration K =1 and Fingerprint Error Threshold = 5 produced the best result in our experiments.

In total, we collected 10 fingerprints in an area of 129.6 square meters. The fingerprint cost is only 0.078 fingerprints per square meters.

4.2.3 Pedestrian dead reckoning (PDR)

We implemented PDR in the mobile app. PDR requires a starting point, a compass, and a step counter. We use the real-time position determined by triangulation as the starting position. We used the gyroscope and accelerometer in the mobile phone to realize a compass. We used the step counter hardware in the Nexus 5 phone to count steps. However, we observed from the GUI that often after the user has taken a few (5 to 10) steps, the position is far away from the user's real position. To investigate the reason for this, we separately examined the accuracy of the step counter and the compass.

4.2.3.1 Performance of step-counter

We tested the performance of the step-counter in two conditions: when the user is walking slowly(having a speed around 0.7m/s) and when the user is walking faster (with the speed around 1.1m/s). The table below shows the results.

Table 4-11: Performance of step-counter in Nexus 5 when user walking with a high speed

	Distance (cm)	Time (s)	Speed (m/s)	Actual steps	Measured steps	Accuracy
Experiment 1	1800	16.34	1.10	30	33	90%
Experiment 2	1800	15.11	1.19	27	38	59%
Experiment 3	1800	15.77	1.14	30	31	96%
Average	1800	15.74	1.14	29	34	82%

Table 4-12: Performance of step-counter in Nexus 5 when user walking with a low speed

	Distance (cm)	Time (s)	Speed (m/s)	Actual steps	Measured steps	Accuracy
Experiment 1	1800	27.82	0.65	36	37	97%
Experiment 2	1800	25.27	0.71	35	33	94%
Experiment 3	1800	25.07	0.71	34	34	100%
Average	1800	26.05	0.69	35	34.6	97%

4.2.3.2 Performance of gyro

We did two experiments to evaluate the gyroscope of the mobile phone. In the first experiment, the mobile phone is static. We collected orientation data as reported by the mobile phone. We collected the orientation data every 0.1 second and collected 300 samples.

Figure 4-7 shows the frequency of each value. The value that appeared most is 201°, representing only 11% of all the 300 samples. In summary, 46.67% of the values are between 199° and 203°, while 75% of the values are between 195° to 204°.

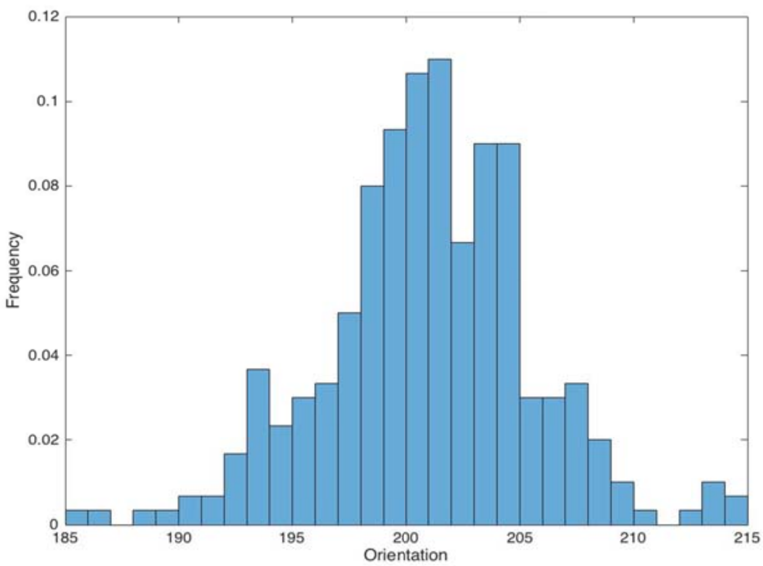


Figure 4-7: Distribution of orientation when the mobile phone is static

In the second experiment, a person holds the phone static in his/her hand. The user can either walk straight forward or stand still. In any case the user is instructed to keep the phone keep facing inthe same direction. We collected 1800 samples of orientation over 3 minutes.

In Figure 4-8 we see that even though the tester is trying to keep the mobile phone facing in the same direction, the motion of the user results in a larger variation in orientation. In this experiment, the most frequent value is 200°, its frequency is only 6.89%. In summary, 30.78% of the values are between 198° to 202°, with 71% of values are between 193° to 207°.

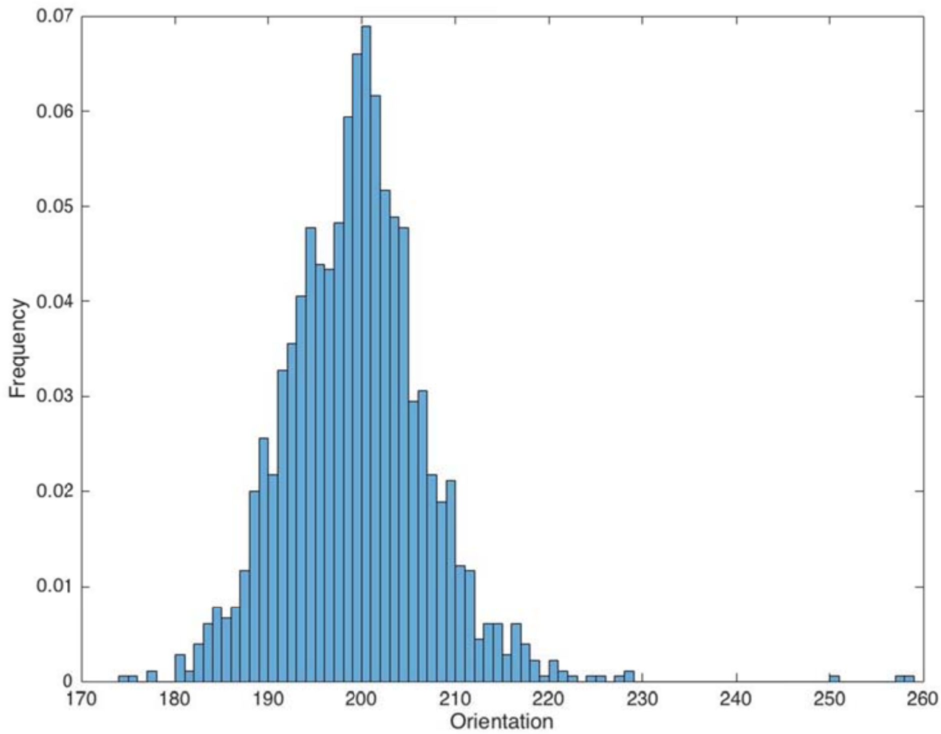


Figure 4-8: **Distribution of orientation when a person is holding the phone while walking**

4.2.4 Implementation of the navigation system and experiments: first trial

Now that we have a positioning accuracy: 1.8 meters. We believe it to be satisfacoty, because our result is better than some (although not all) the existing similar systems described in table 2-2. we decide to extend this static positioning system into a navigation system by adding a user interface and functionality to output audio instructions. Table 4-13 summarizes the design decisions for the user interface.

Table 4-13: Design decision for the user interface design in the first trial

Design decision	Reason
The speed of instruction is moderate.	Different blind users might have different abilities to understand rapid speech. Thus we believe outputing the instruction with a natural speed satisfies most BVI's cases.
Instruction should tell users to "turn right, left, or around".	Blind users might not be able to accurately turn a small angle, such as 10 or 20 degrees, but turning 90 degrees should be easier.
Repeat the same instruction after 5 seconds if the user is not moving.	If the user is not moving, then it might be that he/she missed the instruction, therefore the instruction should be output again. However, it should *not* be output too frequently.
Users have to hold the phone parallel to the ground.	We admit that by asking the user to hold the phone by hand has several drawbacks, as described in section 2.2. However the gyroscope introduces large errors into the orientation if the user does not hold the phone parallel to the ground. Thus we still ask the user to hold the phone by hand. This design should be improved in future work.
Instructions are output via the phone's speaker.	Wearing earplugs might block ambient sound which is important for BVI users.

Then we invited 14 sighted people, covered their eyes with a blindfold.

Initially, we did not give the volunteers any information about the route or the environment. We ran tests with two participants. However, they could not follow the correct path.

Subsequently, we decide to describe the route and environment to participants before the experiment, to help them form a mental map. They are told "You are supposed to walk into the first room on you right, then you should turn left and exit from the other door of the same room. Then you turn right and keep walking straight, until you hear the instruction to enter another room, which is the destination". Table 4-9 shows this path. After giving this information, we tested 12 participants. Most of these participants are able to finish the route within 2 minutes. The average time was 91.7 seconds.

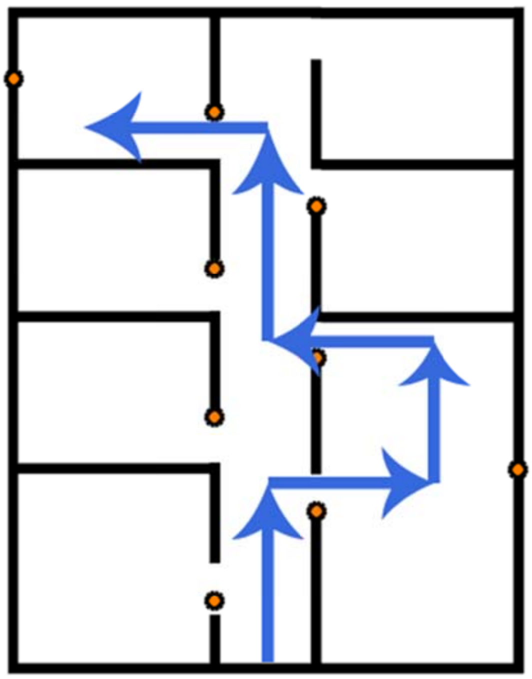


Figure 4-9: **A route of the navigation system**

Table 4-14: **Navigation time for trial 1**

Participant number	1	2	3	4	5	6
Time (s)	90	120	80	80	120	60
Participant number	7	8	9	10	11	12
Time (s)	50	70	210	40	120	60

Overall, these test results were not satisfactory. We believe there are four factors causing this problem:

Volunteers

After the experiment, all the volunteers express they felt some degree of insecure and upset when being blindfolded. As sighted people, they were not used to losing their sense of sight. Being upset made it more difficult for them to concentrate on the instructions; hence they tended to make mistakes. Additionally, these sighted people were not as skilled as blind people when navigating by themselves. For example, when they are told to "turn left and enter the room", some people failed to find the door with the cane even if they are only 10 centimeters away from it.

Replayed instructions	When a user walks too slowly or does not move at all, the same instruction will be output again after five seconds to remind him/her. However, this confused the users. The volunteers seemed to be unable to differentiate between the repetition of an instruction or a new instruction. A solution would be to not replaying the same instruction, unless the user requests it.
Positioning accuracy is not sufficient	Although we achieved a positioning accuracy better or similar to many existing indoor positioning systems, it is not sufficient for navigation. Navigation places high demands on positioning accuracy. In our system, every 1 second the position is calculated and an appropriate instruction is output. Even if we have highly accurate positioning (for example with 80% accuracy), after 4 seconds, the probability that at least one incorrect instruction is output is more than half (59%).
Not utilizing objects in the environment for navigation	We realized that we could have told the user to follow some objects in the environment, for example walls. This would have made it much easier to navigate and to find the doors when the user is told to enter a room.

Seeing that so many aspects of the test could be improved, we decided to change the design and performed another experiment.

4.2.5 Implementation of the navigation system and experiments: second trial

In the second trial, there were many changes and improvements, specifically:

Voluntees	We invited a real blind person to test the system, instead of using blind-folded sighted people.
User interface design	In addition to solving the “replayed instruction” problem, we also included other design changes in the second trial, as per Table 4-15.

Table 4-15: Improvements of interface design

Design decision	Reason
Use reference objects to describe a route	Blind people use reference objects to understand a route
Phone vibrates before playing an instruction	To draw user’s attention before the instruction is output
Give audio information about the user’s position	To make users feel confident and safe
Repeat the instruction on request by double tapping the screen	If the user shifted their attention and missed the instruction, they will be able to listen to it again.
Users will wear only one earphone	Wearing one earphone does not disturb people in the same space with the instructions, while allowing the user to listen to ambient sounds

Algorithm — Since the earlier algorithm we designed did not produce satisfactory results, we tried a new algorithm, i.e., the proximity algorithm.

Environment — In the previous trial, we tested our system in an empty space on a single floor. In this trial, we changed the environment to be a typical office environment consisting of two floors. The user is supposed to enter the building on the ground floor, walk inside, and take the elevator to the 9th floor. When he/she comes out of the elevator, he/she is supposed to enter and walk into the office area. Figure 4-10 shows the route.

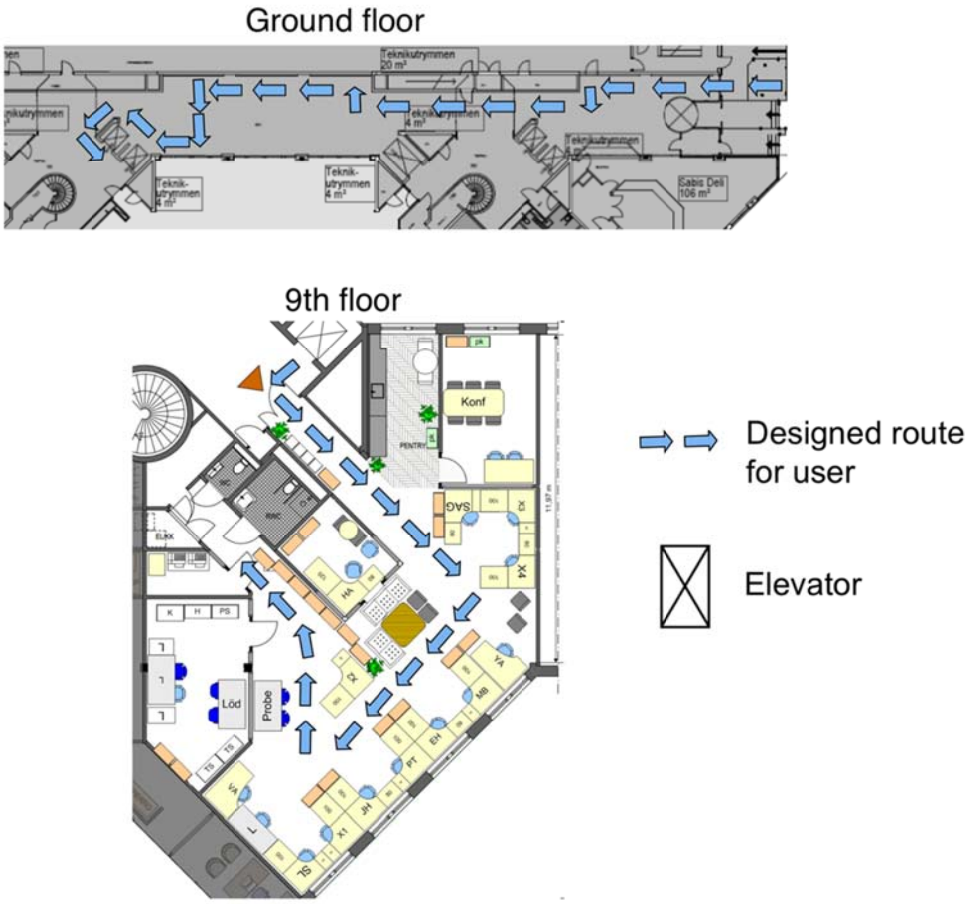


Figure 4-10: Route designed for the blind user

5 Analysis

In this chapter, first we give the results from our experiments and interviews. Next, we analyze these results and compare our system to other systems with similar hardware.

5.1 Major results

In this section, we give the results from the experiments conducted before, including the static positioning result, the evaluation of step counter and the compass, and the results of the two navigation trials.

5.1.1 Static positioning result

Table 5-1 summarizes the positioning result of triangulation under different conditions. Comparing experiments 1 and 3 (or experiments 2 and 4), we draw the conclusion that using pseudo-intersections improves accuracy, no matter whether 9 beacons or the strongest 3 beacons are used. Comparing experiments 1 and 2 (or 3 and 4), we can see that using 3 strong beacons results in better performance than using all the nine beacons. In conclusion, we achieve the best triangulation performance when using pseudo-intersection and beacon selection.

Table 5-1: Summary of static positioning results

Experiment Number	Condition			Accuracy (cm)	Precision (cm)	Failure rate to determine position (%)
	9 beacons	3 Strongest beacons	Pseudo-intersection			
1	YES	NO	NO	424.4	100.4	0
2	NO	YES	NO	268.7	139.3	0.48
3	YES	NO	YES	333.7	49.8	0.08
4	NO	YES	YES	199.8	127.7	0

By comparing the results of all four experiments, we conclude that using pseudo-intersections and use the strongest 3 beacons greatly improves accuracy. The reason for this is that RSSI do not always reflect the distance correctly due to reflection and multi-path effect, hence using less beacons avoids introducing the erroneous information to the system. Using pseudo-intersection greatly improves the performance when the circles often do not intersect. The reason is we do not discard the beacon which does not contribute an actual intersection in triangulation. Using pseudo-intersection, we put a less demanding requirements on the propagation model; thus, even a few measurements with an imperfect propagation model still achieves satisfactory accuracy.

Table 5-2 compares the system's performance with or without the fingerprinting method. When combining triangulation with the fingerprinting method, accuracy improved by 16.9 centimeters and the successful rate to recognize the room increased by 12%, reaching 68%. However, the precision degrades by 23.9 centimeters. This might be caused by the matching fingerprint changed from one fingerprint to another in a short time, since we only choose one matching fingerprint at a time and uses its position as the user's position.

Table 5-2: Comparison of positioning results with and without fingerprinting

	Accuracy (cm)	Precision (cm)	Failure rate to determine the position (%)
Triangulation	199.8	127.7	0
Triangulation combined with fingerprinting	182.9	151.6	0
Comparison	-16.9	23.9	0

5.1.2 Evaluation of the compass and step counter in Nexus 5

From these experiment, we found that the step-counter in the Nexus 5 has satisfactory performance, regardless of whether the user is walking slowly or rapidly.

However, the compass showed very low accuracy. Even in an ideal case, where the mobile phone is static, the orientation values reported were very scattered. When a mobile phone is held in a person's hand, the phone's orientation varies considerably. This variation introduces large errors into the system

To use PDR in a positioning system, I recommend having high quality hardware (both step-counter and gyroscope). Another solution is to definitively determine the user's position once in a while, thus that the accumulated error can be reset to 0.

5.1.3 Results for navigation trial 1

In this trial the test subjects are 12 blind-folded sighted people. The route is 12 meters. The average time to finish the route was 91.7 seconds. Thus the average speed of users was 0.13 m/s.

5.1.4 Results for navigation trial 2

In this trial the test subject is a real blind person. The route is 115 meters. We asked the user to perform the experiment twice. The first time, it took her 6 minutes 9 seconds, while the second time, it took her 4 minutes 48 seconds.

Table 5-3: Result of navigation time

	Experiment 1	Experiment 2	Average
Time (minutes:seconds)	6:09	4:48	5:29

The speed of user when tring the route for the first time is 0.31 m/s. The speed when revisiting the site is 0.40m/s.

After these two experiments, we interviewed the user about her evaluation of the system and the habits of blind users. Additionally, we sought her advice to improve the system.

1. Evaluation of the system

    The user correctly described the route she took. Therefore, she successfully established a mental map of the space. The general impression of the system was "good" and "it helps for sure". The user believes this system will be especially helpful in places that blind users have to revisit, for example hospitals. The user believes that a good thing about the using app is that, by using it blind users do not have to remember every detail of the indoor environment. The user thought it was not difficult for her to use the app and that other blind people who use the phone on a daily basis would be comfortable using the app.

    When evaluating the instructions given by the system, the user thought that she did not understand the instructions perfectly for some time, but after she trying it once, she felt that she could understand these instructions well. In addition, she thought that the instruction "this is the bathroom" was confusing, because it does not tell if the bathroom is on her left side or right side. She mentioned that one instruction "Jonas is on your left" was output several times, which she though might be an error of the system. She liked the speed of the instructions and the idea that we used reference objects to describe the route. She also liked the level of detail of the instructions and thought it was informative.

    The navigation app was correct most of the time. However, it still had wrong estimates and give incorrect instructions. As a result, the blind user cannot depend on this app to navigate, but rather would probably still need help from another human. A very important question was if a blind user would use such a product. The feedback from the one user was positive. She said she would use this product even if it was not perfect for four reasons: First, blind users have to memorize all of the objects and routes in an environment in order to navigate. For example, they have to remember how many meters they should walk before making a left/right turn, etc. With this app, the memorization burden is greatly reduced. Second, this app helps the user find signs in braille. While there are braille signs in some of train stations or shops, unless a blind users knows where these signs they cannot read them. Third, blind people have a strong wish to do things independently. The navigation app gave her a good feeling that she could do things by herself. Finally, the user believes even if the navigation app gave perfect results, they will ask sighted people to confirm it anyway. So having to ask people's assistance will not be a reason to avoid using the app.

2. Advice to improve the system

The advice from the single blind user regarding improving the systems included the following points:

Map learning	Create a 3D audio map that a user can access by tapping on his/her phone. The map should play different sounds corresponding to different objects, hence users could learn about the map by moving their finger over the screen. With pre-learning, when the user actually walks into a space, he/she already knows what the space is like.
Speed of speech	Allow users to select different speeds
Content of the instructions	Besides the currently provided information, the user recommended adding more information, such as the size and the orientation of the room.
Replay instruction on request	The system requires the user to double tap the screen to replay an instruction, but the user though it would be easier to shake the phone.
Use a tiny speaker instead of one plug	Because blind users use both ears to navigate it was disturbing to have something in one ear.

Vibration	After a vibration, the instruction should not start immediately. Therefore, there should be a short time interval between them to enable the user to be ready.

3. Habits of blind users

    In Sweden, many blind people use smartphones, especially iPhones.

    Blind people are very individual. Some people are able to walk very fast, while others cannot. Some people are able to use a clock system for orientation, while others can become very lost. Some people are able to hear very fast speech, while others are not able to do so.

5.2 Reliability Analysis

Reliability is assessed by repeating one experiment for multiple times and comparing between them to verify if they are consistent. As we defined in section 3.5.1, we will repeat every experiment for many times (at least 3 times) until we see that the results have an acceptable variance of 10%. After calcualting the variance in all experiments, we validated that the results are reliable, because all the values have a less than 10% variance to the average value.

5.3 Validity Analysis

We tested the validity of the timer and ruler. Their specification is described in the section 3.5.2.

To validate the timer of the Nexus 5, we used the timer of an iPhone 6. We start the two timers at the same timer and stoped them at the same time. The two timers show the same result, which means that the correctness of the Nexus 5 timer is validated.

To validate the ruler, we used an app on iPhone called iRuler. After comparing and observing that the physical ruler and the virtual ruler in the app has the same length for 1 mm and 1 cm, we validated the ruler.

To validate the software logic, we inputed dummy RSSI to the software. We manually calculate the positions corresponding to these dummy RSSI data, and compared them to the results given by the software. Seeing that the manually calculated results and the results from the software are the same, we validated the software logic.

5.4 Discussion

The result of navigation trial 2 was much better than trial 1 in many ways. In the second trial, the user was not only able to enter/exit elevators to go to different floors, but also the user's speed increased from 0.13 m/s to 0.40 m/s. However, since we changed many design decisions compared to the first trial (user-interface, user, route), we are not able to determine which is the reason that improves the result. The only thing we can conclude that with the design decisions in trial 2, the blind user is able to navigate herself using only the smart phone app as an navigation tool and a cane, without any assitance from other people, and she personally finds it to helpful and user-friendly.

During the interview with the blind person, we gained another important insight that it will be very useful to put Bluetooth beacons on the braille signs. Although there are already many braille signs in different places, they are not fully used because blind people have no clue where these signs are placed. By placing beacons on the signs, the BVI users can easily find them and make use of them.

6 Conclusions and Future work

This chapter draws conclusion about this project and specifies limitations of the result. Finally, some suggestions for future work are given.

6.1 Conclusions

In this thesis, we implemented two indoor positioning systems. The first system uses beacon selection and pseudo-intersection as pre-processing, and uses triangulation and fingerprinting as the main algorithms. It achieves a positioning accuracy of 1.83 meters. The second system uses a proximity algorithm. We also designed a UI which was tailor-made for BVI users for these two systems.

After testing the performance of the positioning system and evaluating the feedback from users towards the UI, we gained several insights. One of these was that accuracy is very different for static positioning systems and navigation systems. While the static positioning performance of the first system (accuracy: 1.83 meters) is not bad compared to other indoor positioning systems that use similar technologies and hardware, it is not sufficient for a usable navigation system.

While it can be difficult to improve the technology used in positioning, there are still many other ways to optimize navigation performance and the user experience. The key is to fully utilize the environmental information. To describe the route using objects in the environment and to instruct users to follow objects (such as walls) in the environment simplifies navigation.

The navigation performance and the feedback of the blind user help us draw the conclusion that: A smartphone (similar to the smartphone that was tested) is suitable as a navigation tool for BVI users, under the condition that the algorithm is proximity and the environment information is utilized in navigation.

Another insight we gained is that BVI users often do not find braille signs because they cannot see where they are placed. Putting beacons on braille signs and using our navigation app will help blind people to find these signs and actually make use of them.

6.2 Limitations

We only tested the navigation system with one blind person. The evaluation of the system would be more convincing if more BVI users were involved in the test.

6.3 Future work

Connecting the mobile phone with a smart watch, and using the step counter in the smart watch for pedestrian dead reckoning might improve the positioning result.

In addition, we tested our system in a relatively small space, with few people walking around. If the system were deployed in a large, crowed space, with many people constantly moving about, such as shopping malls or airports, the accuracy might be reduced, and there should be an improved systematic way to perform route planning.

6.4 Reflections

The volunteers who participated in the tests of the prototype gave their informed consent to participate in these tests.

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