DEVICE-FREE POSITIONING USING A CEILING-BASED VISIBLE LIGHT SENSING SYSTEM

by

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A thesis submitted to the

School of Graduate Studies

Rutgers, The State University of New Jersey

In partial fulfillment of the requirements

For the degree of

Master of Science

Graduate Program in Electrical and Computer Engineering

Written under the direction of

Marco Gruteser

And approved by

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New Brunswick, New Jersey

January 2018

ABSTRACT OF THE THESIS

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Positioning systems to determine the coordinates of a person inside a building or a room have been gaining popularity in recent years. Device-free positioning can be of use in many applications; for example, in a smart home, it would be useful for the lights in the bedroom to turn on once a person enters, and for it to turn off once they get into bed. However, existing solutions need expensive hardware installation, or require the user to hold a device to act like a receiver in order to be positioned, which is inconvenient. In addition, due to factors such as multipath and wall attenuation in closed areas, common localization strategies such as trilateration and triangulation struggle to provide a low localization error. LED bulbs are steadily becoming ubiquitous in modern society due to their energy efficiency and shelf life, so using visible light sensing for indoor localization is a good way to reduce the amount of external hardware needed to be installed. When a person is in a particular location in the room, shadows form on the floor due to the LED lamps on the ceiling. A highly sensitive prototype is designed and developed to detect the exact position and length of these shadows. These unique shadow patterns can be used in turn to estimate the position of the person. Using this setup, a low localization error of 2 feet is obtained. Finally, this setup is compared to existing technology, showing it to be more suitable for these applications while leveraging existing infrastructure.

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Chapter 1

Introduction

This thesis documents the design, experiments, electronic hardware and results concerning a project aimed at achieving accurate indoor localization through visible light sensing. Localization has been a prominent research area for wireless communication researchers, with indoor localization having several challenges to overcome. Device-free positioning plays a critical role in many applications such as industrial asset tracking in hardware stores, location analytics for market feedback in malls and supermarkets, theft protection in banks, and contextual-based services to perform actions in smart homes in response to location information. Since the users are not required to carry any devices, the system cannot use standard localization techniques like trilateration and triangulation. Thus, DfP localization analyzes changes in signal levels due to the presence of a person and makes decisions based on these changes.

Visible light, existing ubiquitously in all indoor rooms, proves to be very useful for a ceiling-based indoor localization system since it is reflective, is blocked by humans, and is harmless. LED light can also be modulated much like RF signals due to its ability to instantly turn ON and OFF with rise and fall times of microseconds. The visible light technique to achieve indoor positioning can be made to be passive in such a way that the humans indoors do not need to hold any devices that would act as receivers or transmitters; instead, it exploits the shadow the person leaves on the floor. Any light falling on an opaque object, such as a person, casts a shadow on the ground. The shadow results in a lower light intensity, and any sensor designed to record the amount of light falling on the ground can pick up this change in light level and report back the presence of a shadow in its range. This project consequently uses an array of visible light transmitters (LEDs) and sensitive photoreceivers to receive this light. The shadows on the floor when the light from the transmitting LED lamps is blocked by the person is enough to provide information of the whereabouts of the person. An algorithm is used to do so.

1.1 Problem Statement

The research problem the project strives to solve is as follows:

> *What is the maximum accuracy to which it is possible to localize humans carrying no additional devices inside a typical office setting using off-the-shelf LED lamps, with only minor modifications contained to the ceiling?*

This project attempts to answer this question through experimental evaluation of a hardware system, and is done after simulating the setup in MATLAB to optimize the configuration of the setup in the room. Testing is done in an exemplary conference room, and the floor of the room can be thought of as the positive X-axis. The desired outcome is the abscissa on which the person is standing on. Closer together the different abcissa the system can differentiate between are, smaller the localization error, which is the error to which the position of the person can be estimated.

The main features of the project include:

- The prototype being completely confined to the ceiling.
- Minimum modifications being done to the COTS LED bulbs.
- Device-free passive positioning reducing the effort required by the user.
- Detecting shadows on the floor
- Localization achieved with +/- 90 cm error, and error rate of 70%

To test the system and quantify its performance, the accuracy, responsiveness, coverage, adaptiveness, scalability, cost and complexity are discussed and calculated, as suggested by Farid et al. in [1].

The accuracy of the system depends on the error rate % , and depending on the cell size chosen, it decreases as cell size increases. By varying several parameters of the setup, these can be minimized, depending on the size of the room. The configuration with a good trade-off on both these metrics would be ideal to perform localization.

The project had two main phases:

1. Designing the visible light sensing prototype to procure data necessary for localization: During this phase, nodes with the capability to be used for visible light sensing were designed and prototyped. These nodes were designed to be very sensitive to changes in light levels, and transmitted data about these light levels to a server.

2. Implementing the algorithms in MATLAB to localize a person using the procured data: Using the data transmitted to the server which reflected the levels of light seen by the nodes, an algorithm is made and used to determine where in the room the person is standing.

1.2 Contributions

This thesis makes the following contributions:

- A Device-free Passive indoor localization technique is proposed using COTS LED lamps and photodiodes that are completely on the ceiling, with minimal changes to the existing infrastructure.
- Several hardware prototypes of the system to install on the ceiling are designed, modelled and prototyped, and the best performing one is placed on the ceiling and used for experimenting.
- The setup is tested and experimented on in different scenarios (changing the distance between receivers and transmitters, using different people) to find its localization accuracy.
- The setup is compared to several existing technologies in the passive indoor localization domain using visible light sensing.

The following chapters explain, in intricate detail, the procedures done to solve this research question.

Chapter 2

Related Work

2.1 Indoor Localization

Detecting the whereabouts of mobile robots indoors has been a prominent research topic since the 1980s, as seen by Krotov [2] in his research on positioning a robot by equipping it with a camera. Localizing human beings without any devices attached to them, however, is relatively new. Active Badges [3] were among the first tracking systems that attempted to locate a person indoors. Developed by Want et al, the technology deployed a local network of sensors that used infrared waves to detect the 'badges' worn by the users. Active Badges had various limitations, such as its low time resolution of 15 seconds due to its low signalling and its line of sight requirement. This was, however, an excellent first step for indoor localization after identifying that GPS was negligibly useful to utilize indoors. Modifications of this were done continuously, inspiring the ParcTab by Xerox [4], a major stepping stone for contextual computing.

There are several ways to precisely locate a mobile station in a room to several feet with a setup of base stations. Such techniques fall under the category of device-based indoor localization. While this kind of localization has been vastly explored, it can be more useful and challenging to achieve device-free localization, where the user is completely passive and positioning is done with the changes in the environment brought about by their presence. Absence of a device on the user side is commercially advantageous, since it keeps the load of infrastructure to the system, and users don't have to carry a sensor or a tag with them. Research has been done in areas of RF-based indoor device-free localization, where RF transmitters and receivers are placed around an indoor space and the channel characteristics provide information about the presence of a person in the signal path. There are other methods of indoor localization, such with ultrasonic sensors, pressure sensors, PIR sensors, etc.

Projects most related to this type of indoor localization can be categorized based on the type of signal used to position as follows:

- RF signals - RFID chips and WiFi
- Ultrasonic signals
- Infrared
- Image signals

2.1.1 Indoor Localization using RF signals

RF signals are long range signals, used in Wifi, cellular networks and satellite communication. The localization aspect of this project was inspired by RADAR [5], an RF based indoor localization strategy developed by Microsoft Research. The user holds a mobile device, and the room has strategically positioned base stations that receive information from the mobile station. RADAR utilizes a predefined database of positions versus their corresponding signal strengths. The database is collected by having a person stand at known locations with a mobile station equipped with an RF transmitter, and collecting the signal strengths as seen by the base stations. When a user stands in an unknown location, the collected signal strengths for that location can be compared to those in the database, the entry most similar to that observed is singled out and used to determine the coordinates of the user.

RFIDs have been frequently used in ubiquitous computing, notable for their low power consumption, compactness and feasibility, can also be used in indoor localization, as elaborated in the following projects.

SpotOn [6], developed by Hightower et al, built new custom tags called ‘SpotOn tags’ based off of RFIDs to use triangulation in computing the fine-grained location of a user. Three of these distances are sufficient to triangulate the desired position. Lateration is the idea behind GPS - knowing three distances of a 1D point from three different base stations is enough for backtracking to where the point is. Distances from base stations are approximated by taking several signal strength measurements and averaging using an aggregation algorithm.

LANDMARC [7] uses reference tags (or ‘landmarks’) that are similar to the base stations in SpotOn, but instead of averaging over received signal strengths from the user, the reference tags output a discrete power level from 1 to 8 based on the received signal strength. The signal strength corresponding to a power level changes dynamically with the environment using an algorithm, advantageous in the presence of changing surroundings. Both SpotOn and Landmarc use Spider systems for optimality.

In [8], Jin et al. analyze the limitations of LANDMARC, namely the unnecessary computations that are done, and the necessity of a higher density of reference tags. They then propose an alternative mechanism to dramatically reduce the average localization error detected by the LANDMARC system. Instead of utilizing all the neighboring reference tags, using k of the nearest tags can reduce the error and reduce interference.

Using RF can be prohibitive sometimes - multipath interference, non-LOS errors and high attenuation make it tempting to search for other methods of localization.

2.1.2 Indoor Localization using Ultrasonic Signals

Ultrasonic waves are sound waves that are of frequencies above the audible range. They can be transmitted and received with ultrasonic hardware. An advantage of using ultrasonic signals is its high level of accuracy, up to mm and cm.

Active Bat [9] , like all previous localization schemes, is fine-grained. Bats are known for their echolocation abilities to hunt for insects in the dark. Similarly, this system uses TDOA (Time Difference Of Arrival) to estimate the distance between the base station and the mobile station, or the ‘bat’. If the time taken for a sound signal to reach a bat from the base station is known, the distance between the two can be calculated from the speed of sound.

There are other projects that use a combination of two signals. For example, Cricket [10] uses a combination of ultrasound technology and RF to find the location of a mobile station, using ‘Cricket nodes’. The concept of Cricket is similar to RADAR in that it has a predetermined database. Doing such combinations of technologies can increase the accuracy of localization from what localizing with only method would allow for.

For larger networks, configuring the base stations of Active Bat and Cricket may be difficult. Dolphin [11] uses a combination of RF and ultrasonic signals, similar to Cricket, but it uses a novel distributed algorithm to make modifications to the base stations easier.

Some problems of using ultrasound for localization are its lack of scalability due to interference issues, expensive hardware requirements, and higher power consumption [12].

2.1.3 Indoor localization using Infrared Radiation

IR can be used in indoor localization, as seen in Active Badges. Pyroelectric Infrared sensors can be used as a line of sight method to detect the presence of people. Yang et al. propose in [13] a method of integrating an accessibility map with the sensor data. The PIR sensors are placed on the ceiling pointing straight down, and are made to output ‘Detected’ when the presence of a person is found within a ring right below it on the floor as opposed to a circle. This is similar to our system, in that it is entirely on the ceiling at the same height. The accessibility map helps fuse information about where the user is most likely to go, which helps improve accuracy. Luo et al. [14] developed a similar ceiling-based method of using PIR sensors, but uses Kalman filters and a localization algorithm to make decisions on corner cases.

The unreliability of PIR sensors stems from the change in heat that can be detected through sources other than humans - a hot vessel placed in the room could be localized as a person due to the IR radiation it emits.

2.1.4 Indoor Localization using Image processing

Image signals can also be used to perform indoor localization, Surveillance is, in a way, a form of indoor localization, albeit a wasteful way of doing so, because of the amount of unnecessary data collected just to locate a person. There have been several projects aiming to minimize the amount of data collected through images.

Another way to position people using image processing is by using markers. This is more of a landmark based approach, and is more coarse-grained.

As previously mentioned in a development by Krotov et al., positioning of indoor mobile robots was an issue that several sought to use cameras for, in order for the robot to interpret its position using images of its surroundings. This was extended to human users, using their camera phones.

In [15], Ravi et al. achieved indoor localization by having their users wear a camera phone around their neck. An algorithm compared the obtained pictures with a pre-existing database. Good accuracy levels were achieved; however, making the database was an hour long process and different heights had to be accounted for.

Other less commonly known methods include using the magnetic field of a mobile device. LocateMe [16] is a fine-grained localization technique that utilizes the built-in magnetic field sensor to find 'magnetic signatures' that can be backtracked to a position in the room. There are many challenges in this method, such as variations in the environment, the presence of metal objects, etc.

SurroundSense [17] is another method that uses various sensors in a mobile phone to perform ‘ambience fingerprinting’ for localization, allowing a diversity that cannot be found in other, more traditional methods. It relies on the fact that every place has its own sound, color and light, and is a coarse-grained method of localization.

2.2 Device free localization

Of the above methods of indoor localization, most methods require the user to hold a hand-held device as a receiver. This is inconvenient in cases where the person forgets to hold the device, or doesn’t want to, or don’t know they are being tracked. In these cases, the user being positioned also needs to be an active part of the positioning. In these cases it is most useful to use DfP, or Device-free Positioning, to compute the desired positioning results by detecting changes in the environment due to the person in question. The following section focuses on these kinds of positioning systems.

One of the most widely known human detection systems is thermal imaging, where a thermal camera is used to detect the presence and approximate location of a person. These cameras can also be very expensive. This is not similar to this project, however, since the transmitter is usually outside the room.

Positioning can be done using computer vision. Depth cameras can be used to localize. EasyLiving [18] uses a stereo camera and a color camera to position people as well as identify and differentiate them. Biswas et al. [19] condensed the 3D point clouds obtained to 2D point clouds, and utilized existing indoor maps estimate what the point cloud would have looked like without a person. In fact, the ground truth for this system’s results was determined using a combination of a Zedd camera and an image processing algorithm.

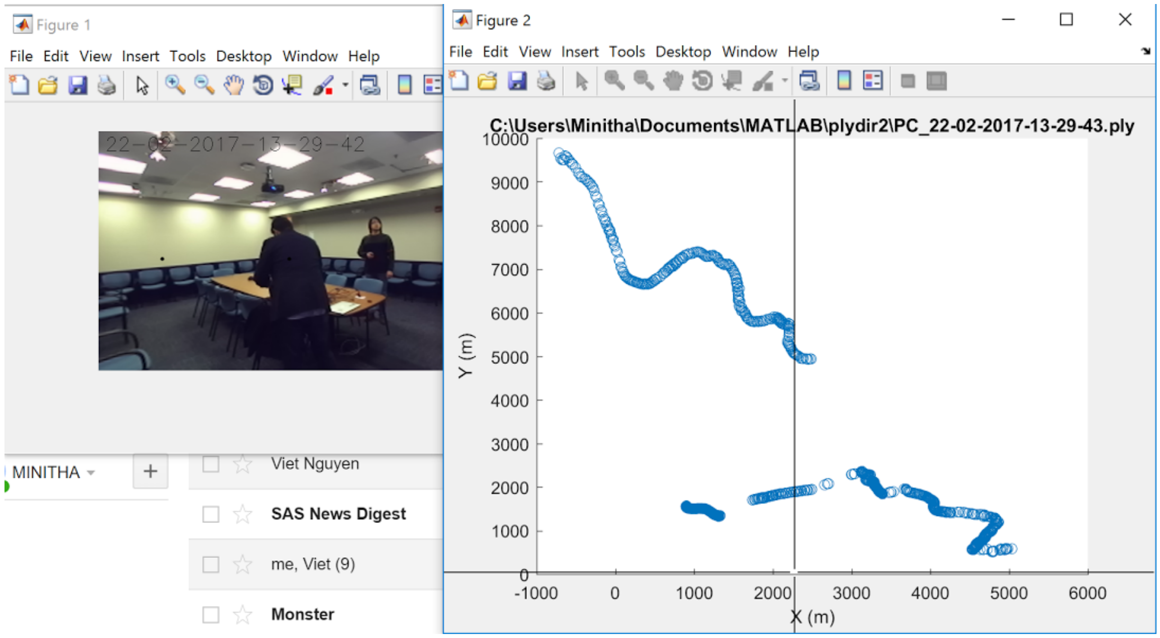


Figure 2.1: Point cloud generated by the Zedd camera due to the position of the person inside the room.

Hile et al. [20] perform a more landmark based localization by comparing pictures to a cached memory bank of known landmarks using an image processing algorithm, and determine what the person might be standing next to.

A disadvantage of extracting features from images to determine positions is the variability of the environment. Other signals are less susceptible to external noise; for example, they are not dramatically affected by someone standing in front of the receiver. Cameras also have privacy issues, and need to be in line-of-sight with the user.

A discrete DfP localization scheme is seen in the ORL active floor [21], using pressure as a mechanism to detect the tile a person is standing on. Each floor tile has load cell sensors under each of its corners, so the most aggregate pressure seen at a tile's corner sensors can correspond to a person standing on the tile. This can be slightly laborious to implement, as the tiles require to be on top of the pressure sensors, so installation can be tedious.

TileTrack [22] uses capacitive sensors as a sort of proximity sensor, measuring the capacitive charge in an electrode as a function of how far the user is standing away from it. It could track users with an accuracy of up to 41 cm, but with several drawbacks such as distinguishing between multiple users and complicated circuitry.

Ultrasonic waves can also be used, as seen by Nishida et al. in [23] where ultrasonic tags are used to perform trilateration to the user. The project also performs experiments to find the best method of trilateration, concluding that RANSAC, or RANdom SAmple Consensus, is the best. In this, three random tags are sampled to perform the trilateration, which minimizes the effects of outlying data.

With the ease in usage of RF signals, there are many systems which employ RF waves in DfP positioning. Nuzzer [24] uses existing wireless RF hardware in an office setting, combating multipath interference using probabilistic models. The 802.11 standard wireless networks are used to measure differences in Received Signal Strength(RSS). A Discrete Space Estimator estimates the expected RSS vector for a particular location in the room using spatial averaging. This localization is also discrete. WLAN is also used for DfP in Ichnaea [25] and Rasid [26].

2.3 Localization using Visible Light: Device-based

LED lamps are ubiquitous in modern society, so it isn't surprising that there are various systems that use visible light in localization. There has been work done in visible light localization using LEDs as transmitters of visible light, and handheld devices such as smartphones as the receivers.

Fluorescent lamps, which are steadily being replaced by LEDs for their efficiency, have their minute bulb-to-bulb differences exploited by Zhang et al. in LiTell [27], where smartphones are programmed to use these differences to localize where it is.

FiatLux [28] has the user wear a wear light sensor as either on a hat or as a pendant, and can detect which room the user is in. This relies on the maximum and minimum illuminations in a room, or the 'fingerprint'. A training phase is required.

Zhang et al. [29], similar to the cases of RF, use the commonly used method of triangulation to discover the coordinates of users on a 2D plane. The power received by a receiver on the floor can compute the distances from four LED lamps transmitting different words. One of the usual problems in triangulation, which is synchronization of all the transmitters, has been eliminated by using slotted ALOHA. A simulation of this proposal concluded a 90% correct estimate rate for 5cmx5cm localization cell. The limitations of this are the assumptions that both the receiver axis and transmitter axis are perpendicular to the floor, and the ideal Lambertian nature of the lamp.

Another technique similar to this is done by Jung et al. [30] , except the distance between the receiver and each of the transmitters is calculated using TDOA instead of using mathematical equations.

Epsilon[31] uses a BFSK (Binary Frequency Shift Keying) scheme in its LED lamps to encode the information of its locations, and with the received RSS at the smartphone, trilateration can be done. RSS is detected using a light sensor that can be plugged into the audio port of the smartphone. In the case there are less than three lamps in the vicinity that the smartphone can detect, some user feedback is taken where the user positions their phone such that it faces the nearest light source, and rotates it in slight angles along the vertical axis. Fusing RSS obtained from these measurements and the IMU sensors (accelerometer, gyroscope, magnetic sensor) can localize a user with up to 0.4m of accuracy.

The CMOS rolling shutter effect is where a picture taken at a particular shutter speed and duty cycle has a particular pattern of light and dark bands, based on the frequency of the light. The frequency of the light transmitted by the slightly modified LED light bulbs is chosen to be greater than 1kHz, making the flicker imperceptible to the naked eye and to cameras. Luxapose [32] uses this effect, analyzing images taken by the user's smartphone for the light beacons, or 'landmarks'. Positioning is done with a landmark recognition algorithm and a database.

These methods do not solve our research question because it the user has to carry a device in order to be localized. In the next subsection, approaches using visible light for DfP are explored.

2.4 Localization using Visible Light: Device-free

DfP localization has been attempted using visible light, where users do not need to carry smartphones or any other handheld devices for their position to be discovered in a room with. Changes in light levels are detected by light sensors and the data obtained is processed and used for localization. To our knowledge, only five systems exist.

Junwei Zhang's system [33] aimed to localize objects such as cars in parking lots and miners in coal mines. He used the principle of trilateration and Received Signal Strength to achieve a localization accuracy of 5.3 cm, by using n transmitting LED lamps each with m beams that transmit a unique ID. The lamps have both transmitters and receivers and are placed on the ceiling,and the receiving photodiodes record the amount of light that is reflected off the object.

iLight [34] uses a mesh of light source and photoreceiver links on walls perpendicular to the wall to determine the height of a person. Determining which links are affected by the presence of the person allows the height to be estimated.

DarkLight [35] uses visible light at ultra high frequencies, so high that it is imperceptible to the human eye, for visible light sensing. This project also uses a similar technique, but does the exact opposite, keeping the LED on for most of the time and switching it off for such a short time users don't notice the flicker.

LiSense [36] uses shadows to reconstruct human postures. An array of photodiodes is setup on the floor, so when a person stands under the LED lamps on the ceiling, changes in the light levels falling on them changes. Each LED (2 in this case) is modulated to a particular frequency for differentiation. The photodiodes are deployed on the floor, which is an infrastructure inconvenience, and is not practical for all flooring material.

CeilingSee [37] exploits the usage of an LED as both a light source and a photosensor, for a setup completely on the ceiling. This is done by redesigning the driver circuit. The diffuse reflection of the light from a person is used to position them. However, dense deployment is required to compensate for the low sensitivity of the LED as a photodiode.

2.5 Summary

None of these methods solve the research questions this project seeks to solve. These are the limitations of some of these localization methods, summarized.

- Localization methods where the user has to carry a device to be localized can be troublesome for several applications.
- RF, ultrasonic and IR radiation methods have errors prone to multi-path interference and non-LOS conditions.
- The environment conditions may change in the room the localization is done in, which are not accounted for.
- Hardware costs are an issue. When expensive sensors are not used, dense deployment is required, which increases installation costs.
- Feasibility of installation is a problem when the sensors are under/on top of the floor.
- Real-time localization is not done, due to the high number of computations required.
- Low localization levels of 2-3m are all that can be achieved.

In the 'Node Implementation' and 'Approach' section, these limitations are addressed, and an approach that can solve all of these problems is devised.

Chapter 3

Approach

3.1 Overview

Again, the objective of this project is to answer the following research question:

> *What is the maximum accuracy to which it is possible to localize humans, carrying no additional devices inside a typical office setting using off-the-shelf LED lamps, with only minor modifications contained to the ceiling?*

To answer this question, a system comprising of a hardware prototype and algorithms to manipulate the data obtained from this prototype is built. The configuration of the prototype depends on the size of the room in which the positioning is performed and the height of the ceiling from the floor. The flowchart in Fig. 3.1 assumes a system of n nodes, each with m receivers.

The node is a unit of the hardware, each comprising of one transmitter and several receivers. These nodes are deployed on the ceiling of the room to detect minute changes in

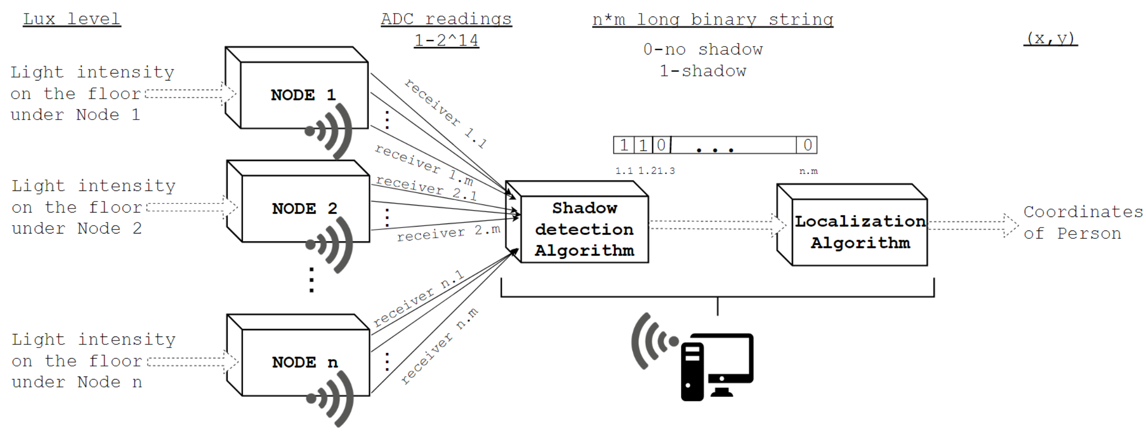
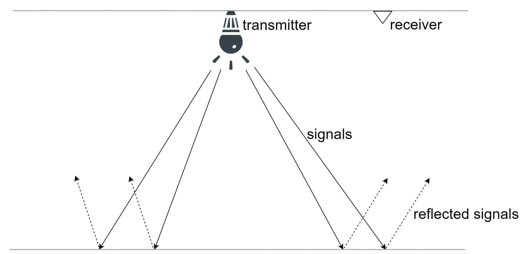


Figure 3.1: Overall setup

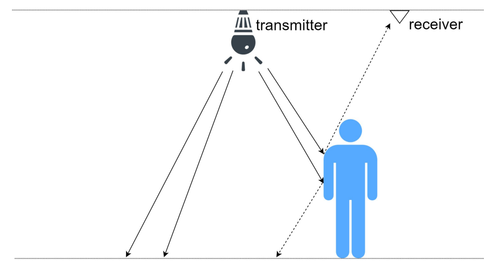
light levels on the floor, so they collect data about the spots on the floor they are pointed to. The design of the prototype used in the experimental evaluation is further described in the 'Node Implementation' chapter, where detailed reasoning behind the components used in the prototype is provided. This data is uploaded to a server running a Shadow Detection algorithm, explained in Chapter. This algorithm gives an output of which receivers see a shadow. This is passed on to the Localization algorithm to determine the position of the person.

DfP localization analyzes changes in signal levels due to the presence of a person and makes decisions based on these changes. Light is reflective, and any light falling on an opaque object, such as a person, casts a shadow on the ground. The shadow results in a lower light intensity, and any sensor designed to record the amount of light falling on the ground can pick up this change in light level and report back the presence of a shadow in its range.

A number of transmitters and receivers need to be kept across the ceiling of the room to gain coverage of the entire floor. Several receiving sensors are installed together with



(a) Received signal with no person



(b) Received signal with person

Figure 3.2: Concept of DfP localization. The physical obstruction of a human being causes some transmitted signals to reflect off their body, as opposed to the case where the signals reflect off the floor/objects in the room. Changes in the received signal strength of the signals at the receiver can be used to detect the presence of a person.

one transmitting LED lamp, each photosensor pointing to a different spot on the floor. The floor is divided into square cells.

The aim is to be able to deduce which cell the person is standing on, based on the light blockage. The photodiodes (the receivers) pick up shadows left by users by observing the difference in light level at the spot on the floor it is pointed at. Based on the set of photodiodes that can see the person's shadow when the person is standing anywhere in a particular cell, the system can localize the person by narrowing down which cell the person is standing in. Prior knowledge of these sets is required, which is why the sets of photodiodes or 'signatures' of the cells is predetermined and stored. Real time data is compared to this database and the signature closest to the observed signature corresponds to the cell the person is standing in.

As noted before, there needs to be several transmitters in the room, and the system needs to know which shadow is caused by which lamp. A time division multiplexing scheme where each lamp modulated with a different offset pulse is used for this, allowing the system to calculate which data comes from which lamp. This is not used in the algorithm since good accuracy is obtained by just knowing which photodiode can see a shadow and which cannot, reducing the complexity.

3.2 Shadow-based localization

This section illustrates how information about the position of a person is obtained using their shadow. Using the shadow of the person allows for Device-free Positioning. Before processing to obtain localization results, the node reports whether or not a shadow is seen by the photodiode. For better noise tolerance and error that could arise due to light level fluctuation at the transmitter and noise at the ADC of the microcontroller, the information obtained is binary, i.e., the system is designed to return the data shown in Fig.3.3 for manipulation at the algorithm stage.

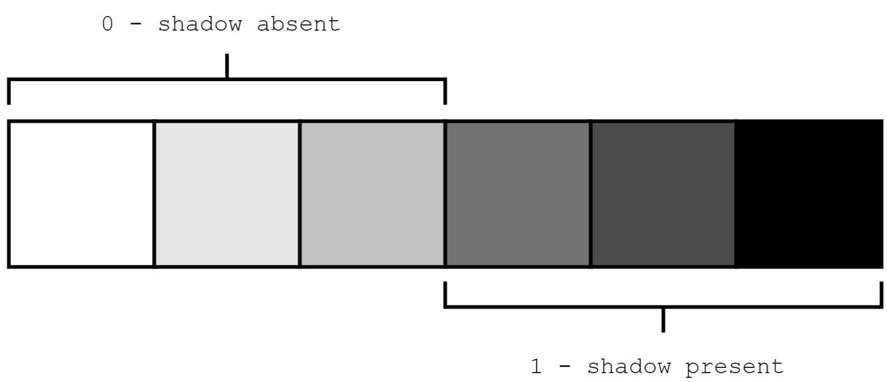


Figure 3.3: A threshold value is determined to decide whether a shadow is present or not.

Fig. 3.4 shows the processes that go on for the system on the ceiling to be able to read the presence of a shadow. The photodiode on the node picks up the light level on the portion of the floor it is pointing to. It translates this light level to a feeble current of several milliamps, proportional to the amount of light on the floor. This current needs to be further translated into a larger voltage for it to be a) processable and b) readable by the ADC of the microcontroller. The circuitry in the node converts the photodiode current to a voltage, sends it to the microcontroller in the MSP432 to be converted into a 14 bit binary sequence that can be transmitted through an onboard WiFi module. The server receives this sequence, along with the corresponding timestamp denoting the millisecond the reading was captured, and depending on the received signal, it can be determined whether the receiver saw a shadow or not.

The purpose of using visible light as the localizing signal and a setup that detects the shadows of the person as opposed to the actual person is the benefit that the user doesn't have to be directly under the receiver in order to be detected; it's enough that the receiver can see some of its shadow, and depending on the position of the person with respect to the lamp, the shadow can elongate to several feet. This resolves LOS problems, allows the photodiodes to have smaller visibility of the floor and consequently leads to better accuracy of localization.

For an intuitive explanation, a person walking along a line directly under an LED lamp as in Fig 3.5 is considered. Light rays will be blocked by the presence of the person and a 'shadow' will be formed; this shadow is due to the blockage of one LED lamp's light, and the floor beneath this shadow may be illuminated by another neighboring lamp. Since the light from each lamp can be distinguished at the receiver, the shadow can be observed.

Depending on the position of the person, the length and position of the shadow due to the lamps change. This is the basis of how different positions can be differentiated from

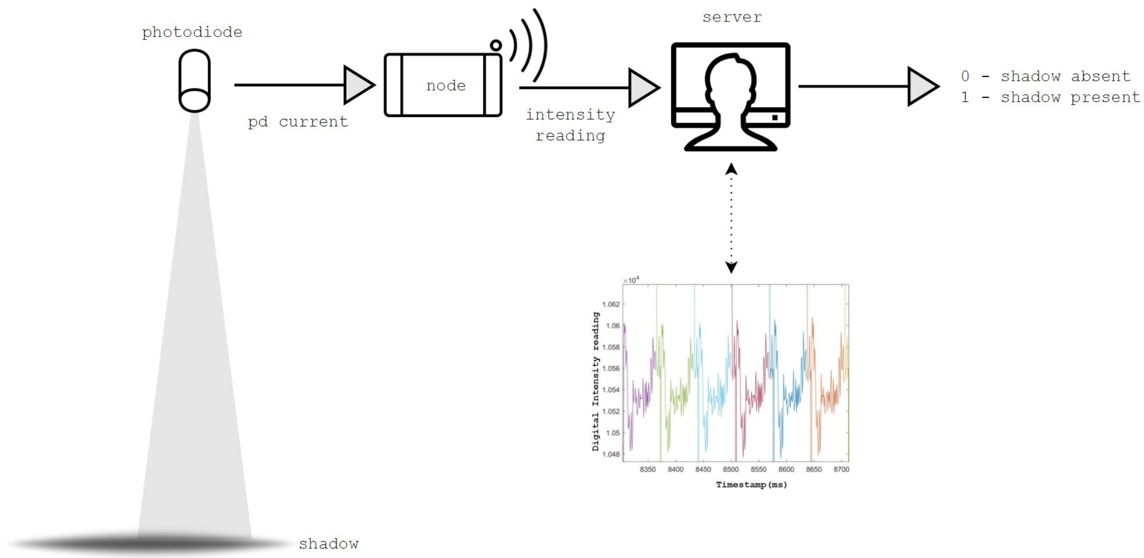


Figure 3.4: Process flow of getting an illumination output of 0 or 1 with the floor as input

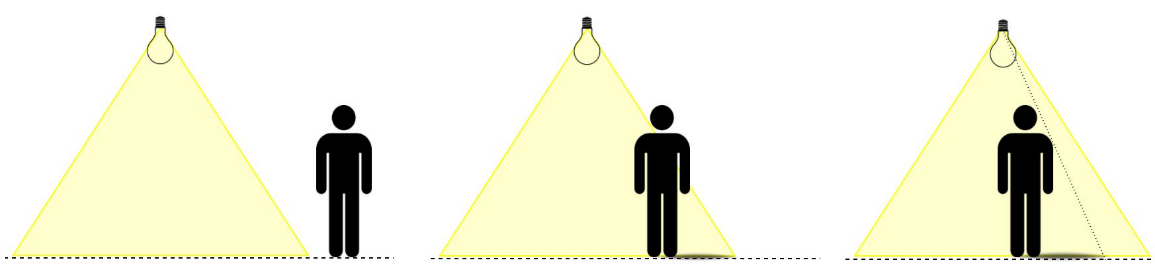


Figure 3.5: Information can be retrieved from the intensity of the shadow(more accurately, the silhouette, at the points on the floor the receiver records data from. This is the property of light to be blocked by an opaque object is its path due to reflection.

each other. The setup, as described in the 'Node Implementation' section, comprises of several nodes, each containing one transmitting COTS LED bulb and several receivers. The receivers have an elliptical visibility region of the floor since they are tilted at an angle to the normal of the floor. The light level is recorded and processed by the node.

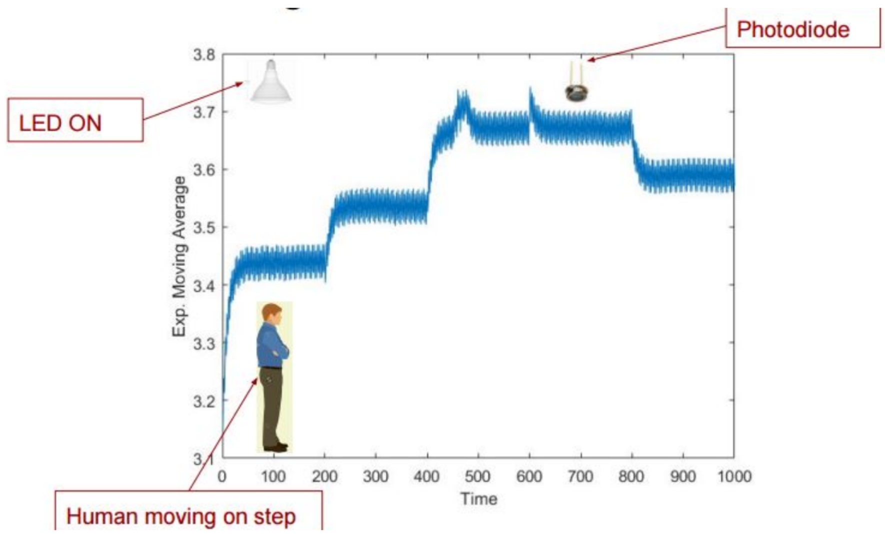


Figure 3.6: The following diagram shows the analog reading at one photodiode when a person stands at different positions. The Y-axis denoted the raw voltage, and it clearly shows that the reading changes depending on the position of the person. This is the main inspiration behind trying to use light levels on the floor to estimate the position of a person.

The photodiodes do not need to have complete coverage of the floor, unlike the transmitters ideally should. The transmitters are characterized with their angular beam angle α, and the greater α is, more coverage of the floor is possible. This is where the inverse-square law of light comes to play. This law can be applied since the LED lamp can be approximated as a point source from the floor, which is far away from the ceiling (9-10 ft). The receiver only needs to record the level of light at several points on the floor.

The inverse-square law states that, due to a point light source, if the intensity (lumen per meter squared) of a point at distance d_1 from the light source is l_1, and the intensity of a point at distance d_2 from the light source is l_2, then it can be stated that

$$\frac{l_1}{l_2} = (\frac{d_1}{d_2})^2$$

In simpler terms, the light intensity at a point due to a point light source is quadratically dependent on the distance it is from this light source.

The flicker needs to be unnoticeable by the people in the room, so the following scheme is used to flicker the lamps. This is in addition to the ambient light of the room due to sunlight or other light sources. This way, at any point of time, a maximum of one LED lamp is turned off, so the light level does not dramatically change due to the flicker. Each box represents one time slot, and each cycle is 8ms long. Once all these time slots are completed, the cycle starts again. In order to accommodate all the lamps, each cycle must have 2N time slots, where N is the total number of nodes on the ceiling. In the current setup, the sampling rate is 1 MSPS (million samples per second) at the ADC.

The light from the lamps need to be differentiated so that the light level change seen by one bulb is recorded. Otherwise, even if the light from one transmitter is blocked on the floor, another light in another part of the room floods the shadow, so the photodiode on the ceiling will see no change.

The light level directly translates to the analog voltage V_{out} that the node sends to the ADC to convert into a digital reading. This digital reading is 14 bits long, so there are 214 or 16384 levels of light that can be differentiated by the node. This reading, along with the timestamp is sent through WiFi to the python server, which can handle data channels from the multiple nodes.. For this project, all further processing is done offline in MATLAB, but further improvements can allow real-time estimation using the same hardware.

Lamp 2, 3, ... N ON Lamp 1 OFF	All lamps ON	Lamp 1, 3, ... N ON Lamp 2 OFF	All lamps ON	...	Lamp 1, 2, ... N-1 ON Lamp N OFF	All lamps ON

Figure 3.7: Timeslots in the implemented prototype. Adjacent time slots are compared to obtain information about changes in light levels from a single LED.

Adjacent timeslots are compared to isolate the shadows that arise due to single lamps. This alternating scheme allows for the light on the floor from all the light sources other than the one in question to be subtracted out. For example, to see the shadow due to lamp 3, slots 6 and 7 in the received signal will be taken and compared. The sampling rate is 1 MSPS, but to reduce buffer requirements, an average of the samples taken during the slot, and this is the value sent to the server. Doing so reduces the amount of data transmitted. If the difference between the average signal level at slot 6 and slot 7 is above a threshold value, a shadow is determined to exist in the photodiodes visibility. If a shadow exists, then for that timestamp (accurate to the millisecond) a '1' is returned. Otherwise, a '0' is returned.

In this project, the LED-photodiode setup is compactly designed as a node, and the system, which comprises of several nodes, is completely ceiling based. Eyelight doesn't require dense node deployment, only requiring 6-8 nodes for a 24ftx18ft room, and is completely contained to the ceiling. Based on simulations and experimental data, an accuracy of 80cm can be obtained.

Chapter 4

Fingerprinting & Algorithms

4.1 Introduction

The main purpose of the algorithms is to use the data obtained from the nodes deployed on the ceiling to determine the location of the person. Upon obtaining information about which photoreceivers can see a shadow for a given instant of time using the shadow detection algorithm, an algorithm is used to estimate which division on the floor the person is standing on. To do this, the unique signatures of each division are obtained using a MATLAB simulation. The system reports an observed signature, which in turn is used as input to the localization algorithm. The algorithm needs to provide an output of which division the person is standing in. The following topics are covered:

- An fingerprinting database of positions on the floor vs. expected shadow patterns
- An algorithm to determine the position of the person using the observed shadow patterns from the database created in the previous algorithm

- An algorithm to decide whether the data obtained by the photoreceiver corresponds to a shadow or not
- An algorithm to configure the setup to the dimensions of the room

This chapter discusses these algorithms in depth, with the reasoning behind the steps and the flow of the processes involved.

4.2 Creating the Database: Shadow vs. Position

This section talks about how to make a fingerprinting database with a one-to-one mapping of the position vs the expected shadow. It is possible to use the property of light to be reflected off of some materials and not off of others, along with the inverse-square law of light rays, to estimate where the shadow of a person will fall, relative to their position below the light transmitters. The reflective property of light is used to estimate the shadow patterns due to a person standing in a particular location, and the inverse-square law of light is used to decide whether the light from the transmitters covers the entire floor or not.

When a person stands in a position on a line, say p, as shown in Fig. 4.1, given the position of the transmitting light sources, it is possible to determine where the shadows will fall using trigonometric functions and the assumption that the light from the transmitters floods the entire floor. This is a safe assumption to make, since LED lamps tend to have a wide light range,

This algorithm considers a room of length l, and two nodes setup directly above the line on the floor along which the person is to be positioned, at a height of h. The spacing of the

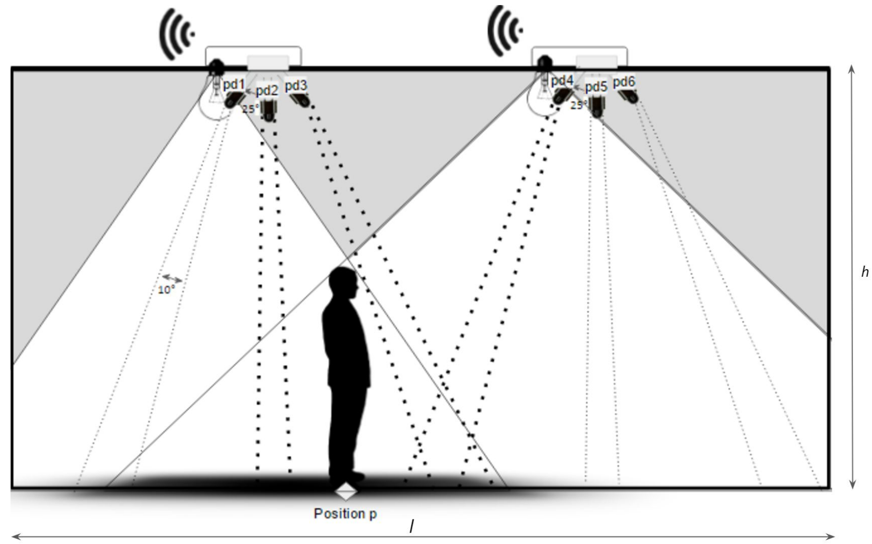


Figure 4.1: A person standing at position p will block the light from nodes 1 and 2, creating a 'shadow'. The position of the person can be determined using this shadow. When a person stands at position p, the photodiodes pd2, pd3 and pd4 can see the regions of the floor that the lightbulbs cannot see, which is due to the obstruction of the person. Based on the exact receivers that can see this shadow and back-calculating using this information, we can estimate the position of the person.

nodes on the ceiling is considered as s. Then using the property of light being obstructed by a person standing in its path, the following formulae are used to determine where on the floor the shadow will fall. To construct the database, the nearest node is determined, and the distance from this node is calculated. This distance is termed as d_{nn}.

Shadows are formed when the light rays from the LED are blocked. The LED lamps usually floods the entire floor of the room, but to accommodate the most general room, an LED lamp with an angular beam of half-angle α is considered. If the position p is to the left of node 1 or to the right of node n, this means the entire shadow will fall on the floor

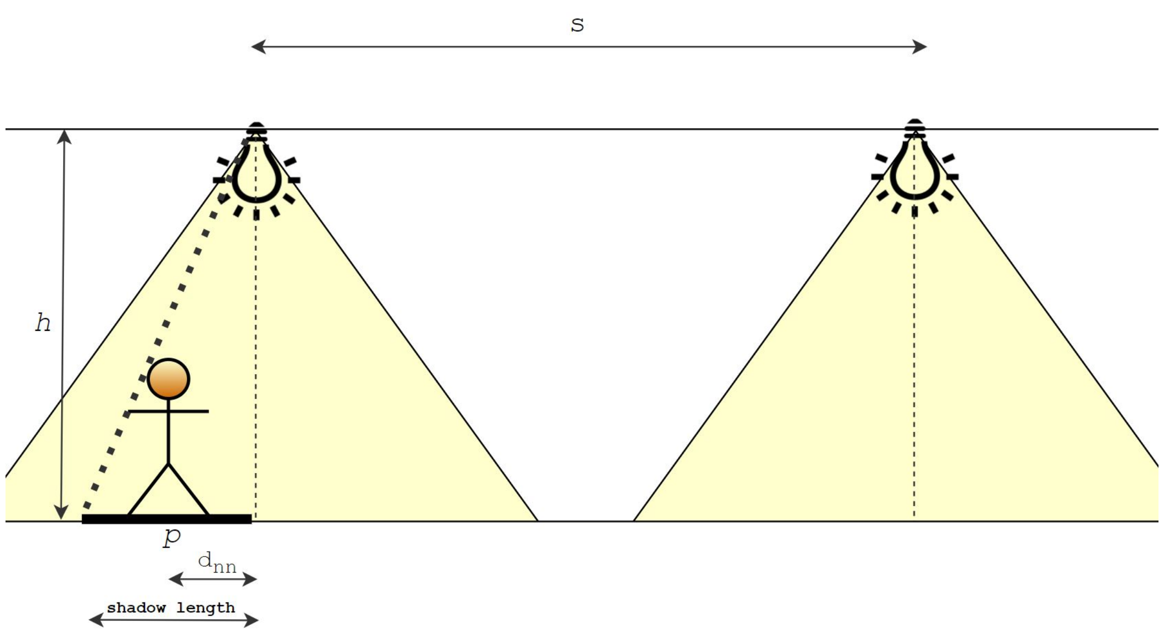


Figure 4.2: In a room of length *l*, height *h*, LED angular beam half-angle α and spacing between nodes *s*, the shadow of a person at position *p* can be estimated. Here, no. of nodes n=2, and no. of receivers per node m=3.

either to the left of the p to the left of node 1, or the right of p, to the right of node n. With this, two cases are possible:

1. the full body of the person is inside the umbra.
2. part or whole body of the person is outside the umbra.

where the umbra is the region of light. The average height of a person is considered to be 5.5 feet.

Case 1: $d_{nn} < (h - 5.5)tan(\alpha)$, or the entire person is inside the umbra of the LED lamps.

Then the shadow length is $5.5 * d_{nn}/(h - 5.5)$.

Case 2: $d_{nn} > (h - 5.5)tan(\alpha)\ \ d_{nn} < htan(\alpha)$

Then the shadow length is $9 * tand(alpha) - d_{nn}$.

Case 3: $d_{nn} > htan(\alpha)$ The person is in a blind spot, and the configuration of the nodes must be changed.

In the other scenario, where the person is the right of node 1 and to the left of node n, where at least two node transmit light that cause a shadow on the floor.

In this scenario, the two nearest nodes are determined. Consider these nodes as i and $i + 1$.

Let the distance of the position of the person from these nodes be d_i and d_{i+1} respectively. Then, since the shadow of the person will always originate from the person and extend in the direction opposite to the lamp causing the shadow, these lengths are calculated by the formulae

$$5.4 * d_i/3.6$$

towards node $i + 1$ and

$$5.4 * d_{i+1}/3.6$$

towards node i.

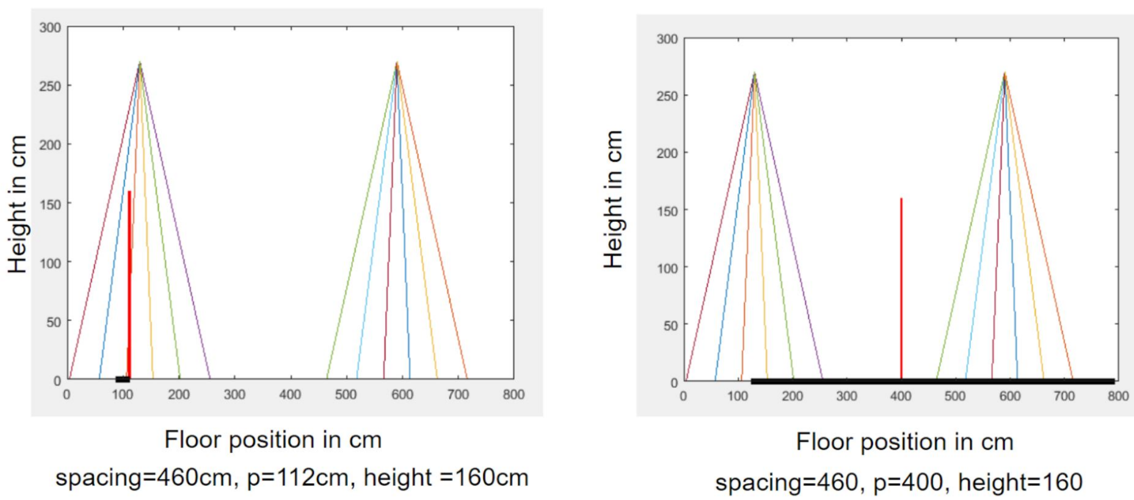


Figure 4.3: It is possible to estimate where the shadows of a person will fall due to the LED lamps. The dark red line is considered to be a person, and the colored lines mark the range of photodiode visibility. The lamps are not denoted and α is considered to be $90 \deg$

It should be noted that for the sake of reducing complexity of the algorithm, the shadows are not differentiated according to which lamp created it by the localization algorithm. However, for the receiver to be able to detect a shadow, the light from each lamp needs to be differentiated, which is why it is modulated. Otherwise the light will be additive on the floor and they it will not be possible for the node to differentiate the shadow from the light of any nodes.

The simulation is done in MATLAB R2017b, by dividing the floor into fixed 1 ft lengths, and then investigating whether each length satisfies certain mathematical equations, given the positions of the transmitters.

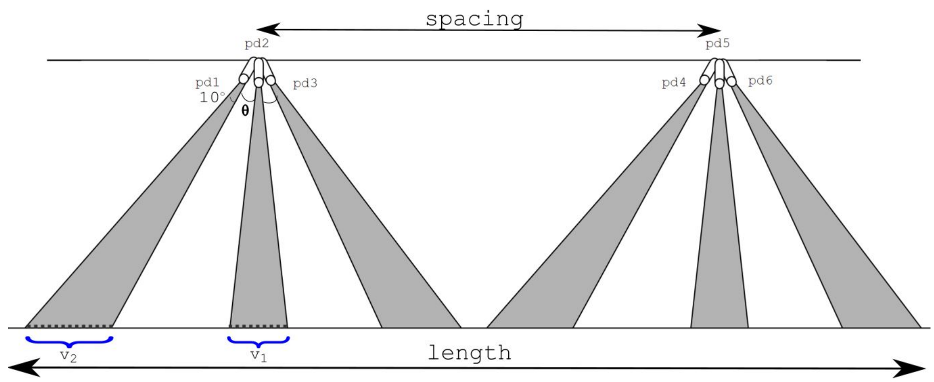


Figure 4.4: Illustration to help explain the trigonometric functions for the database. No. of nodes *n*=2, no. of receivers on each node *m*=3, height of the room is h.

Depending on the angle θ that the receiver is inclined to the normal of the room, the visibility region on the floor of the receiver can be determined as

$v_1 = h * tan(\theta + 10) - h * tan(\theta)$ at a distance of $h * tan(\theta)$ from the point on the ceilings the receivers are connected. This is illustrated in Fig. 4.5.

Since the length of the line on which the positioning is to be done is known, first the simulation divides the ground into an array of structures, each with an integer variable *shadow* and an array *pdvisibility*. Each element in this array represents a foot of the ground. If a photodiode can monitor the light level on an element, that the bit corresponding to that photodiode is assigned as 1. For a particular position, it is possible to compute which lengths on the ground will have a shadow using trigonometric functions. For that position, the ground elements with a shadow falling on it will set its *shadow* variable from 0 to 1.

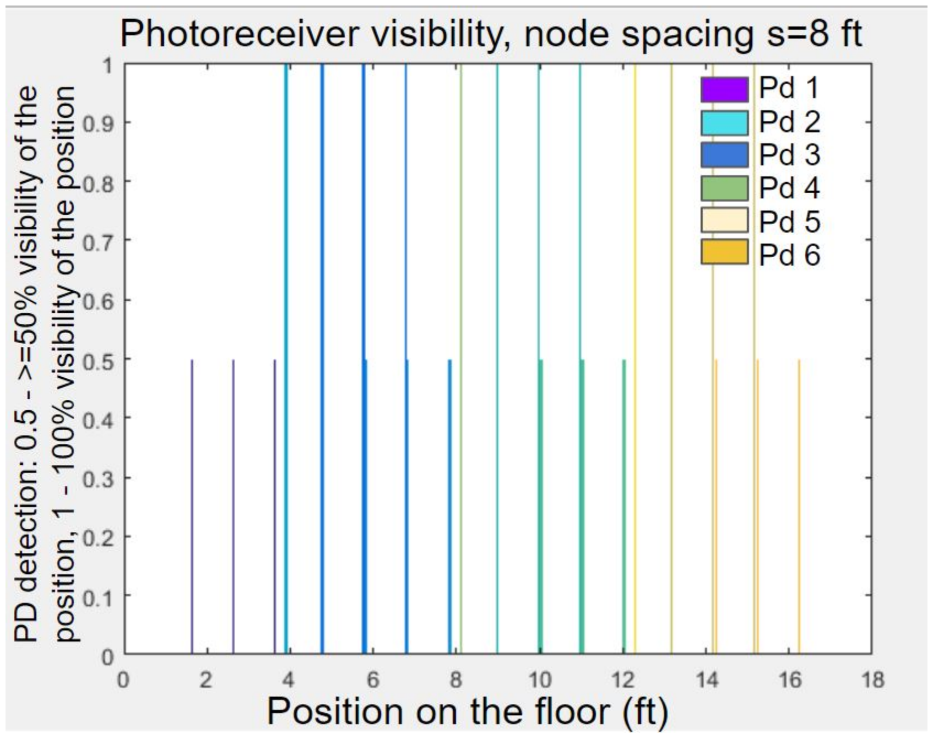


Figure 4.5: Based on the angle of the receiver to the normal of the floor, the regions of the floor that the receiver can see can be calculated. If the entire element on the floor is visible by the receiver, the visibility is set as 1. If it is partially visible, it is set as 0.5. Otherwise, it is set as 0. This information is stored in the *ground* array of structures, in the *pdvisibility* array.

Using the information, a two-phase step is performed: checking which elements on the ground the person's shadow falls, and then seeing which photodiodes have visiblity of that element.

If the receiver has visibility of the shadow of a person at that position, then the signs database bit for that position, for that receiver is updated.

A sample signs database is included for reference. This ability to characterize each location in the line as a unique set of receivers is the core of the system.

Division no.	Rx 1	Rx 2	Rx 3	Rx 4	Rx 5	Rx 6	Rx 7	Rx 8
45	1	1	1	0	0	0	1	1
56	0	0	1	1	0	0	1	0

Figure 4.6: Sample *signs* database

4.3 Localizing Algorithm

A localizing algorithm is developed to determine the whereabouts of a person based on where their shadows are. The nodes pick up light intensity at certain regions on the floor, and based on which sensors detect a shadow and which sensors don't, the position can be backtracked. The 2D case where the person stands on different divisions of the line is taken. The lengths of the divisions are taken to be 2 feet. Once the *signs* database is formed using the MATLAB simulation algorithm, the observed signature needs to be compared to each one of these unique signatures to find out what is the best estimate of the division number the person is standing on. The *signs* database is a mapping of the position versus this set of photodiodes, so looking up in the database the set of photodiodes seeing a shadow, the position can be found.

Division no.	Sign
1	1 0 0 0
2	1 1 0 0
3	1 1 1 0
4	0 1 1 0
5	0 1 1 1
6	0 0 1 1
7	0 0 0 1

Figure 4.7: Sample signs database

The nodes on the ceiling along with the shadow detection algorithm obtain information about which sensors detected a shadow for a particular timestamp. There are many different ways to compare an observed signature to a database of signs; finding the minimum euclidean distance, or the minimum manhattan distance are a few traditional methods. These methods were tried and then tuned to a more suitable method for this particular system, where the positions of the sensors are known.

If the observed signature exactly matches one of the entries in the*signs* database, then the algorithm returns that division as the estimated position. If it does not match any of the entries, an additional step of finding the minimum euclidean distance of the observed signature from similar entries with 1 bit varying from the observed signature in the *signs* database is calculated, and the entry with the least distance is decided to be the position. This is more suitable as it takes into consideration that a nearby receiver may have incorrectly lit up instead of the expected receiver. In case this doesn't work, or a noisy erroneous signature is observed, the average estimated position over the next three consecutive time stamps is taken.

input : Observed Signature, Signs Database, Location of Nodes

output: Division no.

```
initialization;
for i ← 1 to no.of divisions do
    if observed signature=signs(i) then
        division=i;;
    else
        find differing pds;
        if only 1 bit differs between observed signature and signs(i) then
            find euclidean distance ;
        else
            store in buffer;
            calculate for next three observed signatures;
            find average
        end
        minimum euclidean distance← division = i
    end
end
```

Algorithm 1: Localization Algorithm

Thus, using the VLS setup, the position of the person has been estimated. The following section illustrates some sample results for a more intuitive feel for the algorithm, and the next chapter describes various metrics to determine whether or not the system works.

4.4 Sample results

For timestamp 20170226153042, corresponding to February 22nd, 2017, at 3:30:42pm, the Zedd camera reports that there's a person standing at 860.59 mm, which corresponds to division 1. The signature observed is 1 0 0 0. This corresponds to the signature of division no. 1, since it has the minimum hamming distance of 0 from it. The reported result from the algorithm is division no.1.

For timestamp 20170226153039, the Zedd camera reports that there is a person standing at 3065.68 mm, which corresponds to division no. 6. The signature observed is 1 0 0 1. None of the signs in the signature database are the same as the observed signature, so the signs with 1 bit dislocated from the observed signature, but with the same number of non-zero bits are considered. These signs are:

division no. 2 - 1 1 0 0 division no. 6 - 0 0 1 1

The photodiodes that can see division no. 2 are pd1 and pd2. The photodiodes that report seeing a shadow are pd1 and pd4. The differing photodiodes here are pd2 and pd4. The distance between pd2 and pd4 is 5ft.

The photodiodes that can see division no. 6 are pd3 and pd4. The photodiodes that report seeing a shadow are pd1 and pd4. The differing photodiodes here are pd1 and pd3. The distance between pd1 and pd3 is 4ft.

Since the minimum euclidean distance is observed with the sign corresponding to division no. 6, division no. 6 is the estimated division number.

4.5 Shadow Detection Algorithm

For a particular photoreceiver wishing to determine whether, at a particular instant, it sees a shadow or not, the ADC output of the receiver is fed into a Shadow Detection algorithm which subtracts this reading with the average base reading of the room, and then averages these readings over a window. If this average is above a certain fixed threshold, then at that instant, a shadow is said to be detected. The accuracy of this algorithm is calculated by changing the strictness of the threshold and the size of the window.

This is explained in further detail by Ibrahim, Nguyen et al. in [38].

4.6 MATLAB 2D Simulation for Setup

A MATLAB simulation is done to determine how the $divisions$ are determined in a room.

1. Input topology independent variables: theta, length, spacing - this depends on room.
   - theta = angle of photodiode with normal to floor
   - length = length of the room
   - Spacing = separation between the two nodes
2. Divide the length of the room into divisions of 1ft.
3. Based on angle theta, find all the divisions on the floor which the photodiodes can see.
4. Based on spacing, find the placement of the nodes.

5. Start with a minimum division length of length/2.

6. Consider a person of a certain height, standing on the first division. Three heights are considered: 5'4", 5'10" and 6'4".

7. Based on the placement of the nodes, find the divisions of the floor that the shadow of the person falls on.

8. Find the set of photodiodes that can see the shadow. This is the signature of that position.

9. Move the person by minimum cell size divisions and repeat steps 7 and 8.

10. Continue moving the person by minimum cell size divisions and finding the signature for each of these positions, until the length of the room is complete.

11. If all of the signatures are different, decrement the minimum cell size. Else, return minimum cell size+1.

Using the above algorithm, the minimum divison length x which is distinguishable by the setup is found. This is used in the other algorithms as discussed.

4.7 3D Algorithm

The algorithm assuming a 2D case can be easily extrapolate to be used in a room. In practice, the room is a cuboid and the floor is a 24 ft x 19 ft rectangle. Square cells divide the floor instead of divisions. The side of this square is the localization error - which is the degree to which the algorithm can differentiate positions.

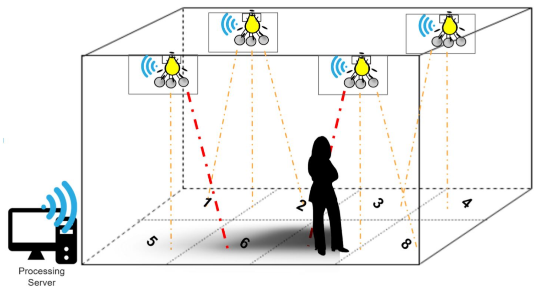


Figure 4.8: A possible setup of the room, with a person standing in cell no. 7.

The results below use the same algorithm, but instead of considering the person as a stick, they are considered as a cuboid, and the floor is a plane instead of a line. Actual localization in this scenario falls out of the scope of this thesis, but will be taken up as a future project.

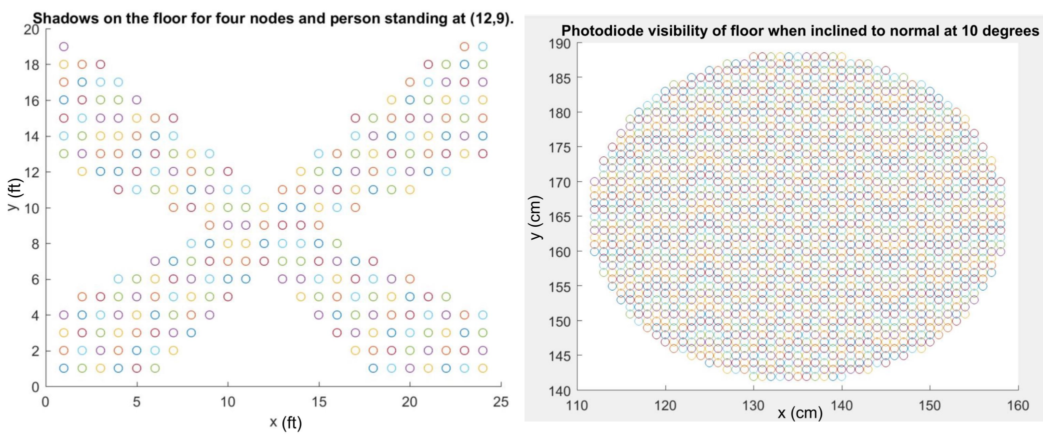


Figure 4.9: a) the portions of the floor on which the shadow of a person standing in the middle of a square room falls, when the light sources are at the corners. b) Visibility of each division from the photodiodes, for the specific case where the nodes are separated at 8ft from each other.

The photodiodes pointing straight downwards will have a circular view of the floor. Due to the inclination of the other photodiodes, the region of visibility will be an ellipse.

Chapter 5

Node Implementation

5.1 Introduction

A prototype is designed and built for visible light sensing. Installing these nodes on the ceiling and setting up the server to receive the data transmitted from the nodes are the only steps required for localization.

Some of the applications the node has been used for include detecting door opening and closing, activity detection, and room occupancy.

This section covers the hardware and software implementation of the node the project uses to achieve the experimentation results required for localization. The node is a compact unit on the ceiling, containing both the transmitter and the receiver of the system.

Since the localization is device-free, the receiver and the transmitter are both on the system side, as opposed to the user-side, and the user doesn't need to carry anything to be localized. The node performs both functions of sending out visible light and receiving the light levels seen on the floor.

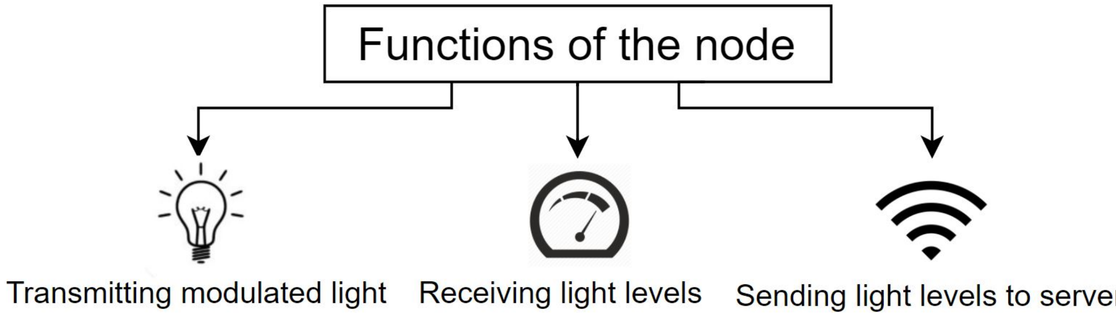


Figure 5.1: The node for the localization project is designed with the intention of a) providing only slight modifications to the LED lamp to modulate the light signal, and transmitting it in that node's designated time slot for synchronization with the other LED lamps, b) receiving the light level on the floor as seen by a photodiode, which translates it to a voltage, and c) Sending these voltage levels to a centralized server for computations through WiFi.

5.2 Transmitting circuit

5.2.1 Flicker

An important goal of the project is for the components in the prototype to be as close to everyday objects as possible, without needing additional expensive hardware. Since the signal whose received strength being tested to indicate the presence of a person is light, a standard LED lamp is chosen as the transmitting device(Fig 5.2). The lamp has 6 high power LEDs inside it.

The nodes are placed on the ceiling, the LED lamps are facing downwards, and the light from the LED ideally floods the entire room if the lamp turns on. The LEDs are slightly modified for the only purpose of being able to differentiate between them. The receiving circuits, also on the ceiling, needs to be able to differentiate between the individual lamps,

(a) Received signal with no person

(b) Received signal with person

Figure 5.2: a) An LED lamp, off the shelf, Ecosmart 65W BR30 LED bulb b) while conducting experiments, the cover of the light bulb was taken off after confirming that the lux level at the floor beneath the covered and the uncovered lamps were the same.

so a simple TDMA scheme is adopted. Instead of continuously emitting the same amount of light, they are modulated to a particular frequency by turning them on and off, as shown in Fig. 5.3.

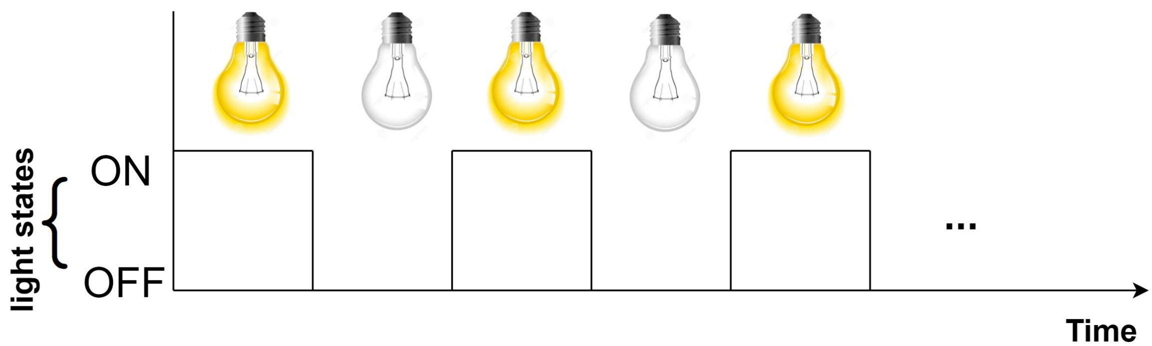


Figure 5.3: TDMA scheme light modulation

The flicker of the lamps turning on and off should be made invisible to the people in the room, so it must be done faster than the response time of the human eye. Any slower and the switching nature of the light could be disturbing and irritating to look at. To decide this, different on and off times were tested and the flicker was observed. We observed the flickering lamp for approximately 20 - 30 seconds before tabulating.

We observe that for longer cycles, when the 'off' time is a thousandth of the 'on' time,the flickering is unnoticeable. However, for shorter cycles, like for 50 ms, a hundredth of the on time is acceptable as the off time. An off period of 1 ms is used in all the nodes, in a total time period of 8 ms.

A higher input voltage corresponds to a higher power input, leading to a higher luminosity. The LED lamps were programmed to flicker by setting an ON duration and an OFF duration and coding the Arduino to switch a FET on and off according to these periods.

All the lamps are modulated to the same frequency, but the time slot at which they turn off is different for each lamp. TDMA systems accommodate multiple signals of the same frequency in the same channel by allocating time slots for each of the signals to be transmitted. For example, if two signals are to be transmitted across the channel, then for a cycle of 10 seconds, the first signal is transmitted for the first 5 seconds and the second signal for the next 5 seconds. Then the cycle is repeated. A receiver at the receiving end would have the information to know which time slot the first signal would be received, and which time slot the second.

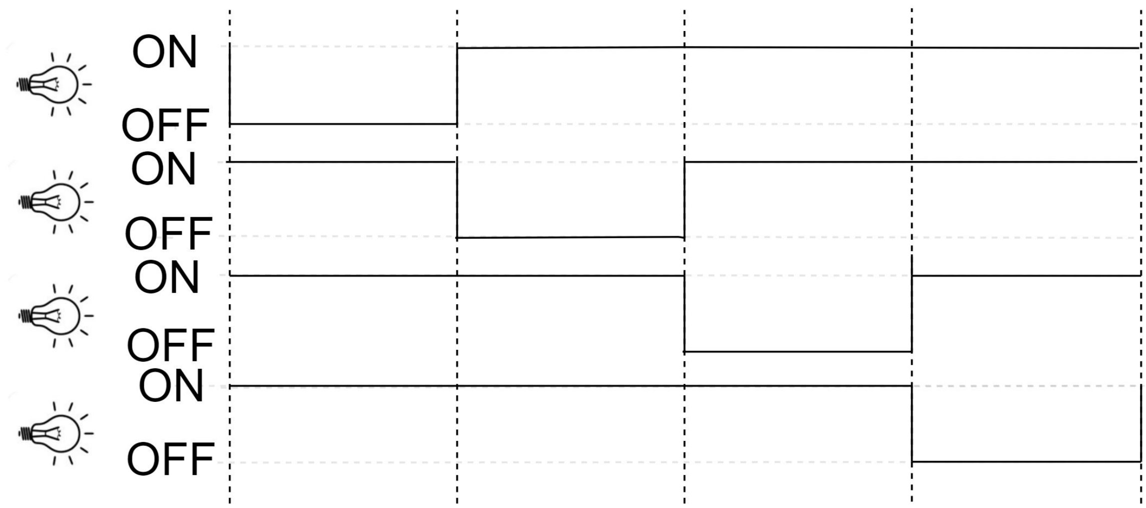


Figure 5.4: LED light modulated to differentiate between light bulbs. The receiver should be able to differentiate between light bulbs, so TDMA modulation is done. To do so, each lamp turns ON almost the whole cycle, except its own time slot. The OFF time of each bulb can be seen as its own light beacon sent to the photosensors: for each time slot inside each cycle, the photosensors read the effect of only one lamp.

This system follows a TDMA scheme for flickering. The LED lamps are turned on for most of the cycle, and are turned off at node-specific slots. Doing this allows for the LED lamps to be distinguishable by the receivers. Each microcontroller connected to a lamp will pick a different time slot for its lamp to flicker. Each lamp is assigned an ID from 1 to N, where N is the number of nodes inside the room. Each node uses its ID as a way to pick a unique time slot to flicker the lamp and avoid collisions with other lamps. Just like in TDMA systems where multiple users can share a medium with the same frequency signal by only transmitting in specific time slots, our system operates in cycles. There is no instant where all lamps are on; if there are N nodes, N-1 lamps will be on at any given time.

Fig. 5.4 shows a picture of the On-Off slots of a system with 4 lamps. This cycle repeats, with the fourth lamp switching on and the first lamp switching off.

Using an optocoupler, the synchronization circuit converts this signal to a square wave of the same frequency and feeds it into the microcontroller.

The rising edge of this square wave is then used as a trigger to start a new cycle, and the microcontroller uses its internal timer to divide this cycle into N time slots, where N is the number of light nodes in our system. Each lamp has a predefined slot it turns off at.

The Ecosmart LED bulbs have an AC to DC driver circuit in them, which is taken out in this project and replaced with a MOSFET circuit to facilitate flickering. The MOSFET can be thought of as a voltage-controlled switch which turns the LED bulb on and off, depending on the voltage at the gate terminal. The frequency at which the LED bulb should flicker is maintained with the MSP432.

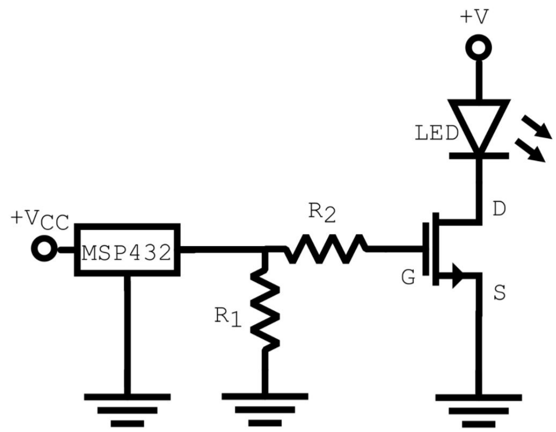


Figure 5.5: A MOSFET is used to toggle the power supply provided to the LED lamp.

5.3 Receiving Circuit

The receiver is the photo-sensing circuit. Changes in the light given out by the transmitting LED lamps on the floor are analyzed to determine the presence of humans. These changes are read by the receiver, which is a part of the node, so installation is simpler and it can be done for all rooms. The receiver is a module along with the transmitter, also on the ceiling. In the current prototype, each node has four receivers, pointed at different regions in the room.

The main component in the receiver is the photosensor, which is responsible for translating the amount of light falling on it to usable information that can be fed into a microcontroller to make decisions based on the changes in light levels. A photosensor is any device that senses light; we require a photosensor that produces a current proportional to the amount of light falling on it. While designing the receiver, different commercial photosensors were examined and tested. Our application required the following qualities from the photosensor:

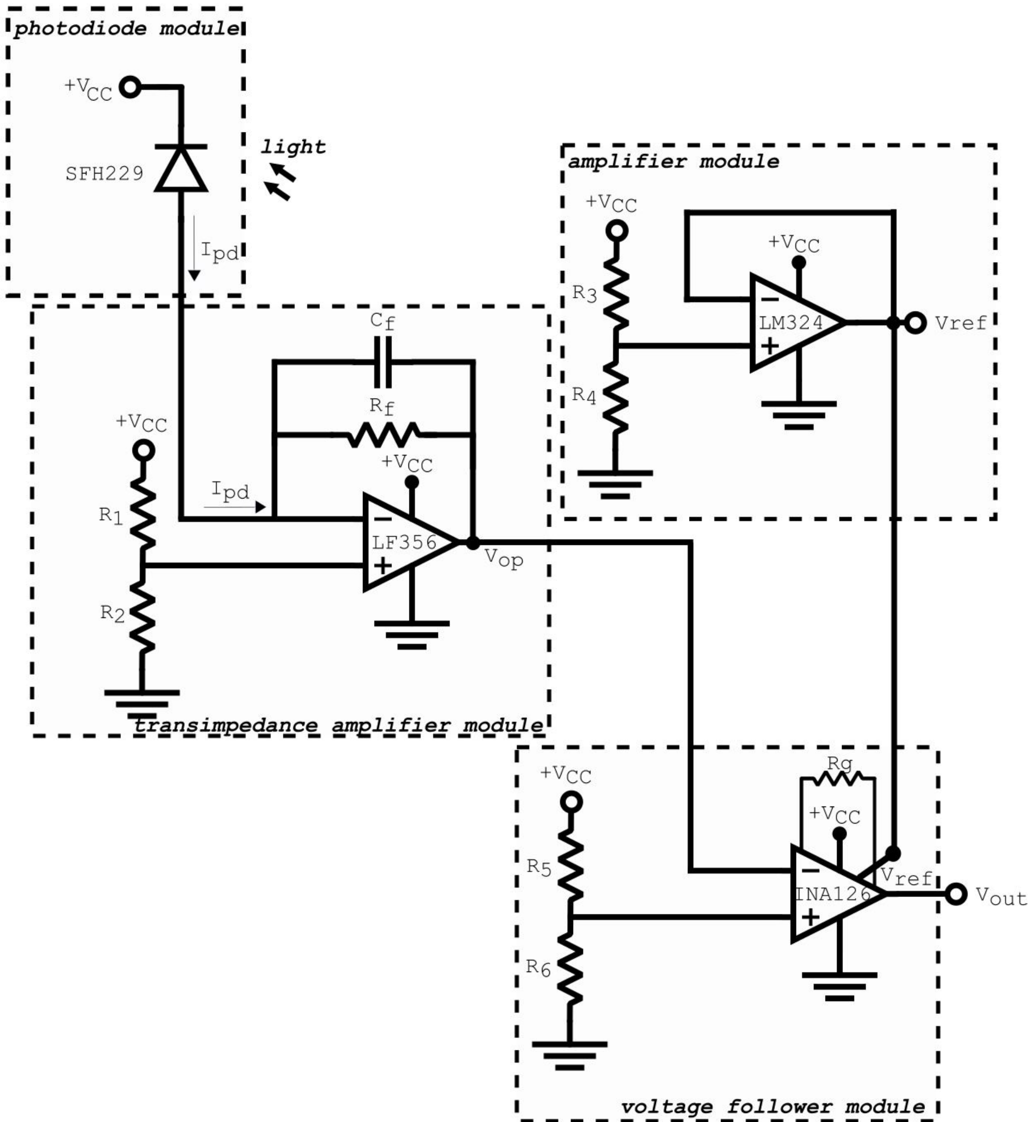


Figure 5.6: The complete receiving circuit. The input signal is the light and the output signal is V_{out}.

- *Should have a high gain* - The changes in light level that are needed to be observed to detect the presence of a person are minute, of the order of 5-10 lx, which should translate to at least a few hundreds of microamps through the photosensor.

- *Should have a fast response* - For optimal data collection, fast switching ability is required by the photosensor. If the photosensor takes a long time to reach its current, reliable data cannot be collected.

This is further discussed in the section below.

5.3.1 SFH229 PIN photodiode

Figure 5.7: SFH229 PIN Photodiode

This PIN photodiode SFH229 showin in Fig. 5.7 was chosen to be used as the photosensor in the prototype. It was tested for the desired gain and response characteristics, and found to fit our design requirements. The node for this project was designed to be used in the WINLAB conference room, appropriate for a typical office setting.

The LED light turns off for 1ms within an 8ms cycle. For the photodiode to recognize this abrupt change in light level from high to low, it must have a fast response time; i.e., the photodiode must have a total rise and fall time less than half of the 1ms off period. The following rise and fall times are observed by using an Arduino powered LED blinking at 1ms ON 1ms OFF intervals.

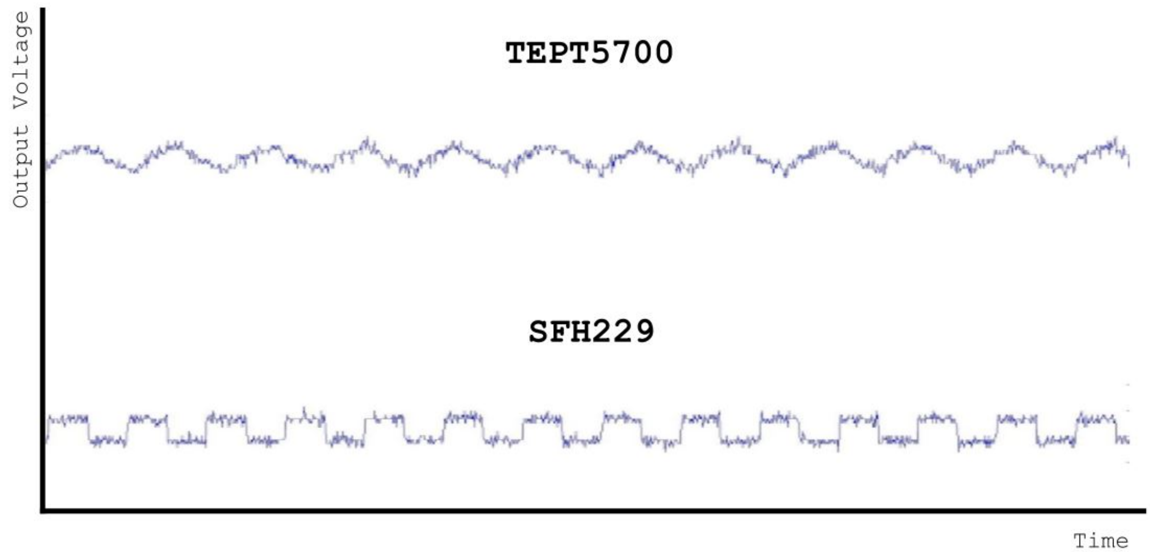


Figure 5.8: The response of the TEPT photodiode vs the response of the SFH229 PIN photodiode, tested using a fast 500Hz signal.

As seen in Fig. 5.13, the SFH229 is seen to have a lower gain than the TEPT, which means small changes in light levels will only change the current passing through the photo-sensor by a few microamps. However, as it can be seen by the output voltage of the circuit with a TEPT photodiode, the fast response of the SFH229 makes up for its low gain. The TEPT cannot be used for applications with many light nodes required in the room, and more information can be gathered using the SFH in the same amount of time.

5.3.2 Difference measurement

The actual level of light seen at the floor is not required - only a difference measurement is. The changes in the light level with respect to the ambient light can provide enough information to decide whether a shadow is present or not. This difference in light level must be carefully extracted and amplified in order to be adequately processed, so a circuit to do so is designed.

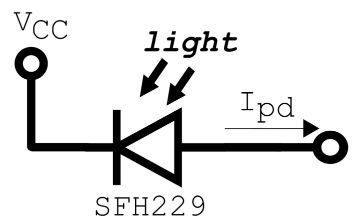


Figure 5.9: The photodiode module. The output of the photodiode is a current of several milliamps.

The output of the photodiode is a current of several milliamps. Recall, the photoelectric effect is what causes current to flow when light falls on the photosensor. Photons, or packets of light, fall on the PN semiconductor junction of a diode connected in reverse bias, and excite electrons from the valence band of the atoms to the conduction band, producing a current proportional to the number of photons that hit the depletion region. There's a threshold to the amount of current a particular material can have, at which it saturates. SFH229 is a PIN diode, similar to a PN diode, but with an intrinsic region between the p-type and n-type semiconductor regions. Having an intrinsic region makes the SFH229 able to operate very well even at very high frequencies. The light falling on it causes a current of Ipd to be produced proportionally.

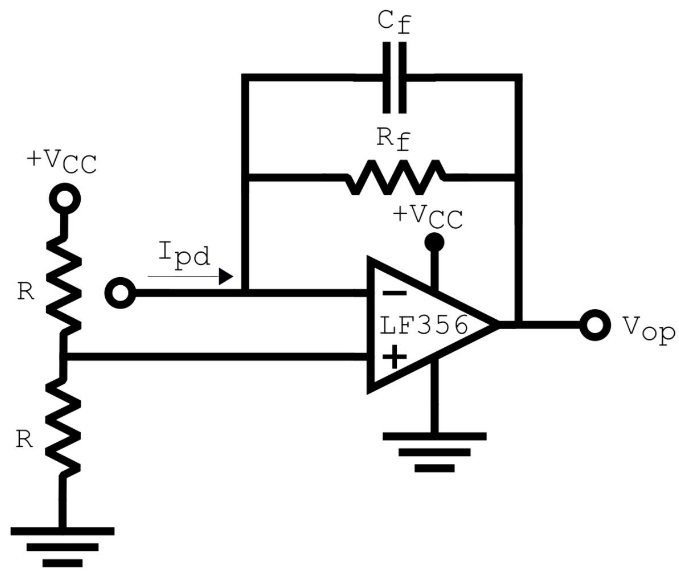
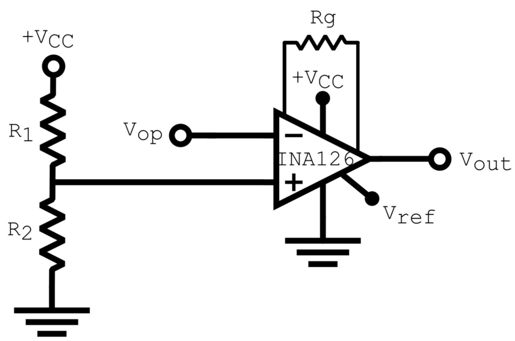


Figure 5.10: A transimpedance amplifier circuit, made from an operational amplifier LF356 and a resistor in negative feedback.

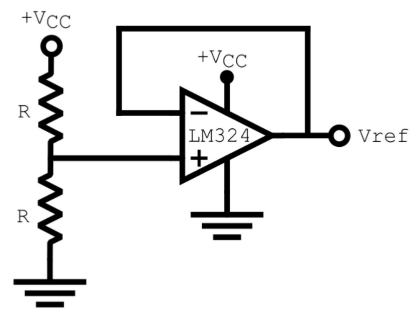
This current needs to be translated to a voltage since processing a voltage is easier than working with current. This is done using a transimpedance amplifier circuit, made from an operational amplifier LF356 and a resistor in negative feedback. As the name implies, the transimpedance amplifier gives an output voltage for an input current. Using a transimpedance amplifier proved to be the best option, since using a lens on top of the photodiode to provide the first stage amplification proved to be practically infeasible.

The LF356 IC needs to have inputs for the inverting and non-inverting terminals. The photocurrent I_{pd} is fed into the non-inverting terminal. The feedback resistor R_f does the function of producing an output voltage such that the two terminals have the same potential. Op-amps have the tendency to produce unwanted oscillations, so a capacitor is connected in parallel to the feedback resistor. This RC combination acts as a filter. The voltage divider circuit at the non-inverting terminal provides a potential of half the biasing voltage, since this voltage will be subtracted from a voltage that corresponds to the ambient light level. This provides a larger range of voltages for V_{op}. A higher I_{pd} results in a lower V_{op}.

$$V_{op} = V_{cc}/2 - I_{pd}R_f$$



(a) The amplifier module



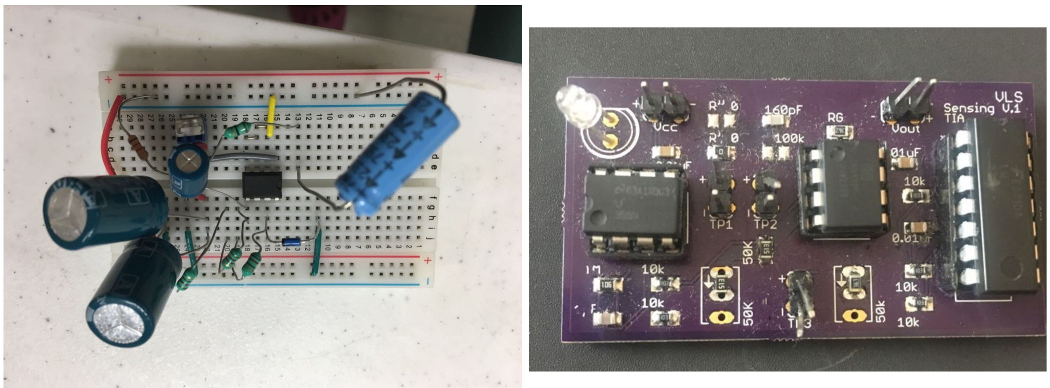
(b) The Voltage Follower module

Since the changes in light levels are very minute, further amplification needs to be done for reliable processing. INA126 is given a reference voltage of $V_{cc}/2$, which means the output voltage will be at least $V_{cc}/2$, i.e.,

$$V_{out} = V_{ref} + G(V_{op} - V_{amb}) = V_{cc}/2 + G * (V_{op} - V_{amb})$$

This is done because V_{out} needs to be positive to be accepted as input to the MSP432, where the analog reading will be converted into a digital reading using the ADC.

The voltage corresponding to the ambient light is given as the non-inverting terminal's input, and can be determined from the TIA during the slot where all the nodes are turned off. In the present setup, we fix it as a particular voltage value for our experiments. In the earlier experimental setups, a calibration step was included to occur periodically to decide the voltage corresponding to the ambient light. Doing this resolves changes in ambient levels due to unforeseen activities like turning off a ceiling light, or opening a window and letting sunlight in. A high amplification leads to a high impedance at the output of the INA126. Current can only flow from low impedance to high impedance, so Vref for the amplifier cannot be given from a voltage divider circuit. A voltage follower stage is necessary to provide a low impedance output. The LM324 performs this function.



(a) Breadboard circuit of the switching regulator.

(b) PCB of the receiver, with the photodiode in the top left corner.

Figure 5.12: Designing phases of the visible light sensing node prototype.

All the circuits are designed, implemented and tested on breadboards. Breadboard circuits are useful during the design phase, to conduct experiments in finding the optimal value of components, and to test different layout of circuits. A design requirement is for it to be the size of fitting into the light bulb if necessary. They are designed in Eagle and printed as 2”x1” PCB boards to be able to do so. Doing this makes the connections more robust, unlike in breadboards where the wires can more easily be compromised.

For values of the components used in the prototype, refer to the Implementation section.

5.4 Synchronization Circuit

Our system relies on the time coordination between nodes, so a good synchronization scheme is needed to synchronize all the nodes with the same clock. The input signal used to synchronize all the nodes is a common sine wave, which can be obtained from the 60Hz AC mains power.

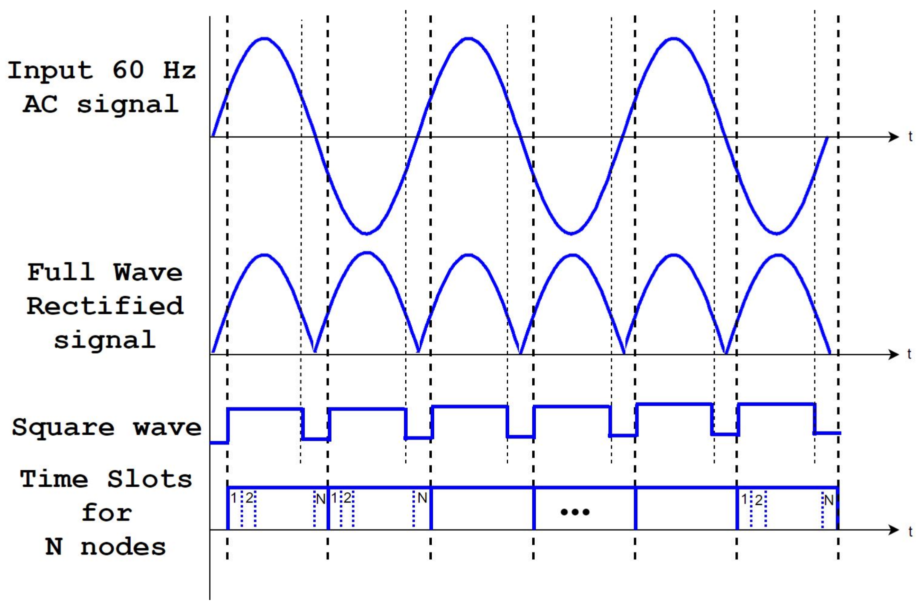


Figure 5.13: The synchronization circuit converts the mains AC signal to a square wave that can be fed into the MSP432.

Using an optocoupler, the synchronization circuit converts this signal to a square wave of the same frequency and feeds it into the microcontroller. The optocoupler also acts as an electrical isolator, making sure there are no AC oscillations at its output. The rising edge of this square wave is then used as a trigger to start a new cycle by being fed into the MSP. The microcontroller uses its internal timer to divide this cycle into N time slots, where N is the number of light nodes in our system. Consequently, all the nodes agree on the timing of each time slot.

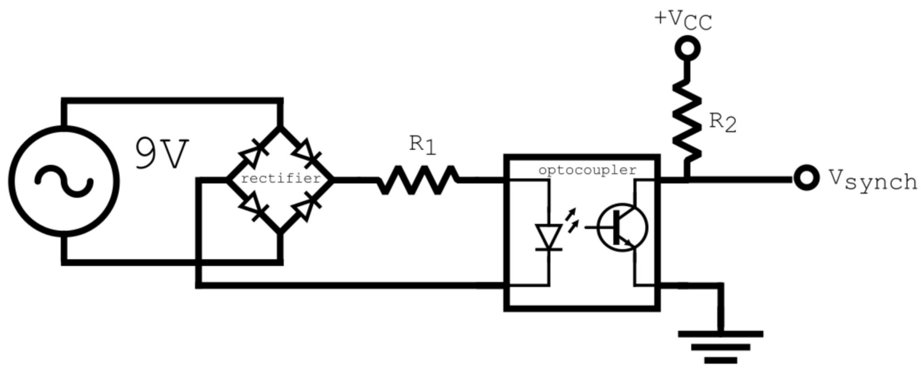


Figure 5.14: Synchronization circuit

5.5 Power Supply

There are many different components that make up the node, many of them active components that need to be powered. These components aim to derive power by stepping down the 110V, 60Hz AC mains signal.

The prototype uses the AC mains as the 60 Hz synchronization signal, and an external DC power supply for the components from a 40V regulated DC power source, which is given as input to the switching adjustable step-down voltage regulator LM2574HV - ADJ. This regulator was chosen because a) a high voltage input needed to be given, and b) different voltages are needed for different components. The ICs on the node need 15V, and the MSP needs 3.3V.

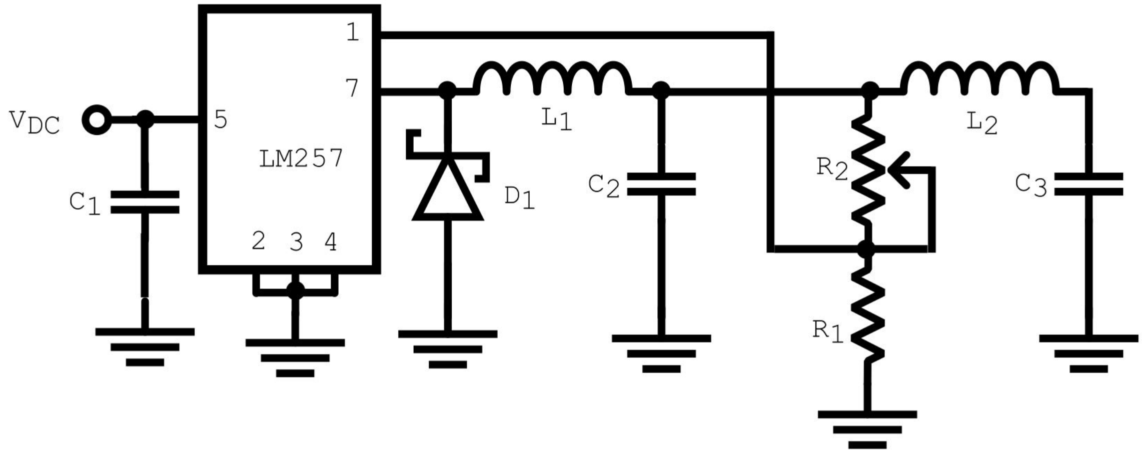


Figure 5.15: This circuit from [39] supplies each individual component with the specific power it needs.

5.6 Microcontroller and Server

The server is a Linux PC that stores the data sent out from the nodes through 802.11 Wifi. A TCP communication is established between the server and the Wifi module on the node. The analog reading from the receiver circuit is converted into a digital reading using the onboard 14 bit ADC. The data required by the server is sent by the MSP432 microcontroller board in a digital format. There is a universal clock on the MSP for all the nodes in the room to be following the same time. Otherwise, the MSP also has the key function of assigning slots to the LED lamps, based on the input synchronization signal.

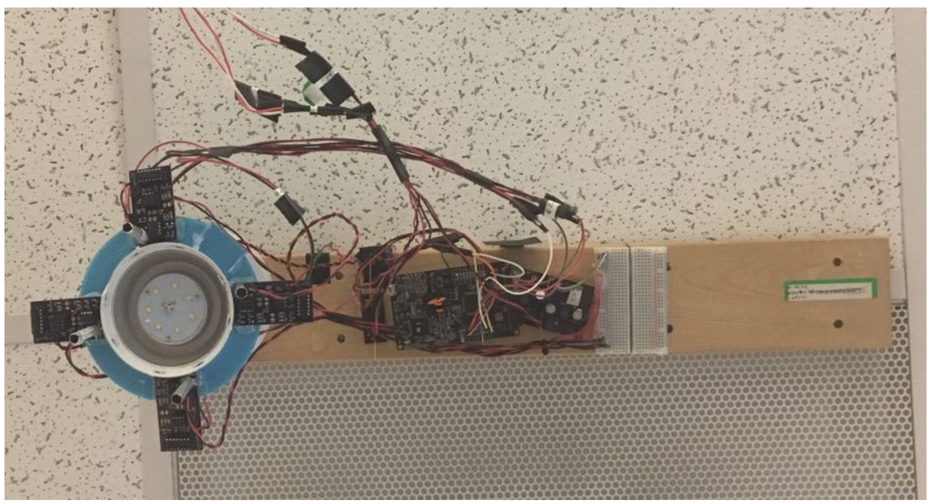


Figure 5.16: The complete prototype of the node on the ceiling.

Table 5.1: Flicker observations

Voltage(V)	Off Time(ms)	On Time(ms)	Flicker Comments
35	1000	1000	extreme flicker
35	100	1000	extreme flicker
35	1	1000	not visible
35	0.5	1000	can only notice if consciously searching
35	0.25	1000	can't see it at all
35	0.125	1000	can't see it at all
35	1000	2000	extreme flicker
35	100	2000	extreme flicker
35	10	2000	slight but visible
35	1	2000	slight but visible
35	0.5	2000	can only notice if consciously searching
35	0.25	2000	can't see it at all
40	1	2000	slight but little more visible
40	0.5	2000	slight but little more visible
40	5	500	very noticeable
40	0.5	500	not noticeable
40	0.25	500	can't see it at all
40	0.5	250	constant mild flicker, not very noticeable
40	1	250	very visible flicker
40	0.5	50	can't see it at all

Chapter 6

Experimental Setup Design

6.1 Design Considerations

For the specific setup for the room we perform testing in, the following table enumerates the values and ranges of the variables in Fig. 5.6.

6.2 The Setup of the Room

If there are N nodes in the setup, and each node has 3 receiving photodiodes pointed in different directions, obtaining the light level at different regions on the floor. The project aims to provide accurate localization results, so optimization would mean less localization error, since the cell size that can be differentiated would be the least it could be. There are several parameters that need looking into before localization can be done. The parameters are:

1. Angle of inclination of the receivers with the normal to the floor

Table 6.1: Component values

Component Name	Component Value
R_1	10kΩ
R_2	10kΩ
R_3	10kΩ
R_4	10kΩ
R_5	50kΩ
R_6	36kΩ
R_G	3.6kΩ
V_{CC}	15V
V_{op}	7.5V
V_{out}	1.67V

2. Distance between nodes

3. Angular beam angle of the transmitter

4. Number of receivers per transmitter

Smaller the least possible cell size, better the localization. There are several objectives to consider when deciding on a cell size for localization. The 2D simulation algorithm considers two nodes in a room which is 24 feet long. There are three photodiodes on each of these nodes: one pointing to the left at an angle, one pointing to the right at the same angle, and one pointing straight down. A cylindrical cover is placed on each photodiode to restrict the area of the floor it can see.

By dividing the floor into *divisions* and calculating which of these divisions the shadow of a person at position p falls on, it is possible to find which photodiodes can see the shadow.

The algorithm finds the minimum *division length* the system can differentiate between given a certain spacing between the nodes and the height of the person to be localized. The division size determines the localization accuracy the system can provide. For this, the *signature* of each position for each division size needs to be found. The signature of a position is the set of photodiodes that can see the shadow of the person standing at that position.

A requirement to differentiate divisions is that the signature of each position is different.

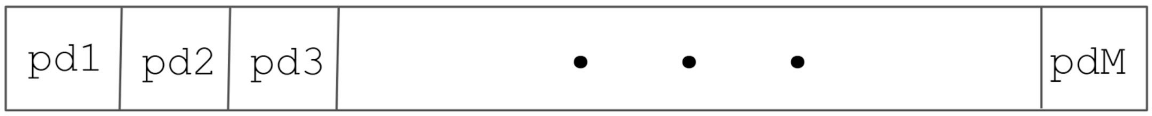


Figure 6.1: The bit 'pd1' will be assigned either a 0 or a 1 depending on whether or not pd1 can see the shadow of a person standing at that cell, and so on. n=2 in this configuration, so M=6.

6.2.1 Angle of inclination of the photodiodes with the normal to the floor

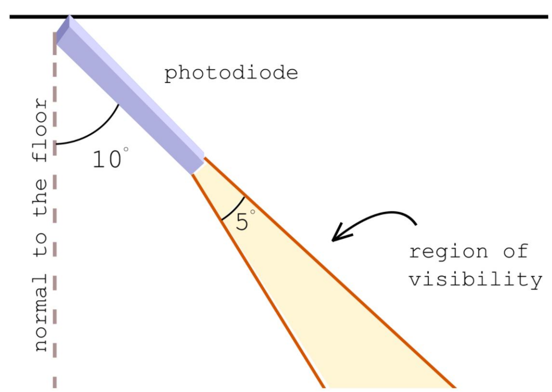


Figure 6.2: Field of vision of a receiver in the setup.

Depending on the angle the receivers are inclined to the floor, they can be made to see different regions of the floor. The following figures illustrate which photodiodes can see which areas of the floor for a spacing of 10 feet, at specific inclinations. All configurations have 3 photodiodes on each transmitter.

To find which areas on the floor are seen by the photodiodes, a MATLAB simulation is done. The following plot shows the visibility of each division from the photodiodes, for the specific case where the nodes are separated at 8ft from each other. If the photodiode sees the entire division of the floor, the value assigned to that division is 1. If only part of the division is visible, the value assigned is 0.5. This differentiation is purely for future purposes, in case partial visibility can be useful data.

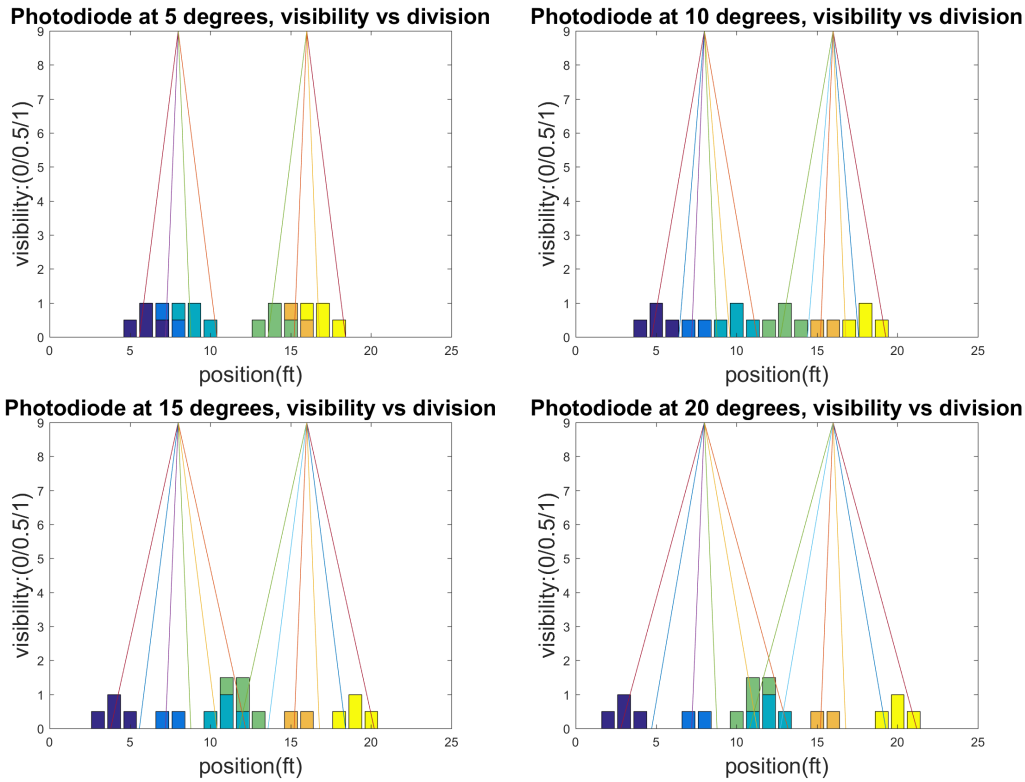


Figure 6.3: a) Visibility of each division from the photodiodes, for the specific case where the nodes are separated at 8ft from each other.

10 or 15 degrees of inclination can be chosen, since the visibility of the floor from the photodiodes seems uniformly distributed. In these configurations, no two photodiodes unnecessarily look at the same region of the floor.

6.2.2 Distance between the nodes on the ceiling:

The minimum possible division length depends upon the spacing of the nodes from each other as well. The figures above show the minimum division length for different inclinations of the photodiodes, different heights and different spacings. It can be seen that 10

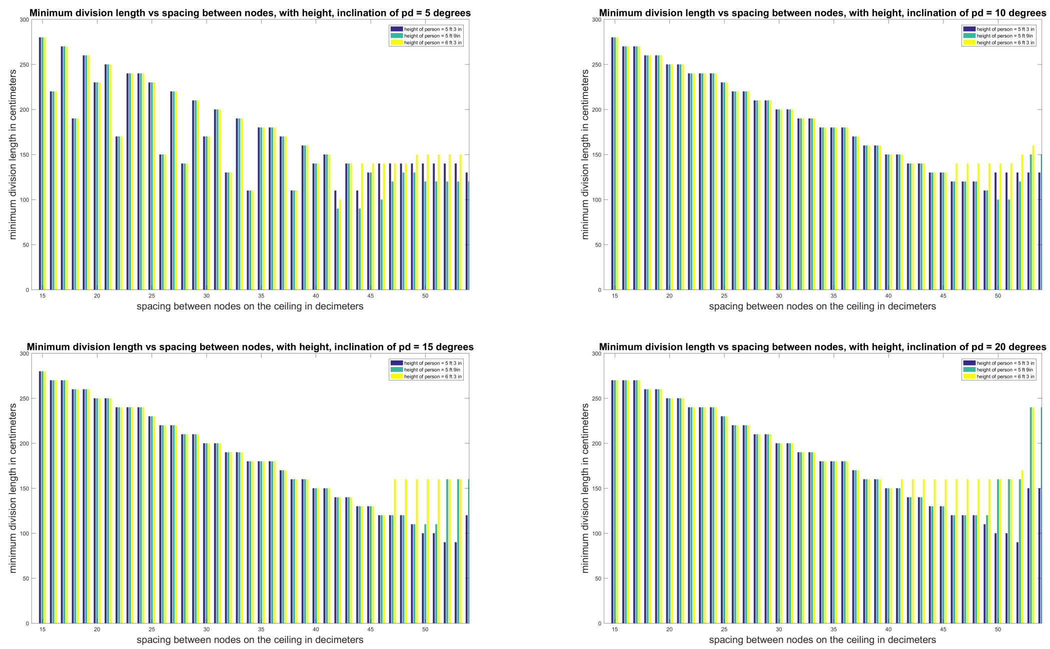


Figure 6.4: The minimum division length for different inclinations of the photodiodes, different heights and different spacings.

degrees receiver inclination pans out for all heights at lower division lengths. The height of the person should not affect the size of the division.A spacing of 350 to 450 decimeters would be optimal. Further testing is done to confirm this.

A receiving photodiode is placed at 8 ft, 12 ft and 16 ft distances on the ceiling from the flickering LED lamp. The dips observed need to be prominent for a good system, so that the events of a shadow being present and a shadow being absent are easier to differentiate. It results in an upper bound on how far the nodes can be placed from each other. The plots in Fig. 6.5 show the received signal at the receiver, at a distance of 8 ft, 12 ft and 16ft respectively.

Since a spacing of anywhere between 8-12 feet seems to be optimal, a spacing of 10 feet is chosen. The nodes are placed at (600 mm,5600 mm) and (3600 mm,5600 mm).

6.2.3 Beam angle

The plot in Fig. 6.6 depicts the observed lux level versus distance of the point from the center of the transmitter. As it can be seen, the light floods the floor to a level that is detectable by the receiver, as shown in the next graph.

The beam angle α is taken as 90 degrees.

6.2.4 Minimum cell size possible

The minimum cell size determines the ability of the system to do localization. For the current scope of the project, 2ft of division length is chosen to allow for some error, aiming for 60-70% localization accuracy. The metric that is given more importance is the scalability, since only 4 receivers are deployed.

Several assumptions are held. First, even if a division is partially visible to a photodiode, the algorithm assumes it is completely seen. Since the divisions are 1 ft long and the photodiodes are sufficiently sensitive to small changes in light intensity, this is viable. Second, we consider an ideal case, where the light from the lamps covers the entire room. While performing experiments where only the two nodes were turned on, it was seen that the light from the nodes is sufficiently intense to cover the entire room. Third, we assume that the photodiode is tilted at the required angle based on the way it looks. These assumptions are safe to make during the design.

6.3 Experiments done

According to the configuration of the room, which has a ceiling of 9 feet and a floor that is 24 feet x 19 feet, the algorithm to determine where the nodes should be placed on the ceiling and the division length that can be confidently distinguished is decided. The nodes are setup accordingly on the ceiling. People are then made to stand in predefined locations, and a Zedd camera is set up to record them in the room. An image processing algorithm runs on the video footage, generating point clouds. These point clouds need to be manually post-processed to obtain the exact location of the person for each timestamp. The system returns the location of the person, and using the ground truth obtained from the Zedd camera, the accuracy of the estimated location is determined.

6.3.1 Workload

For the experiments, 5 different people with varying heights walked on the line under the setup of the system on the ceiling. Their actual positions on the line were monitored on the Zedd camera. They were not made to stand at the location, but merely walked around as they pleased, to mimic real-life situations. 85 different time instants were taken at random, and the observations and results obtained are discussed in the following chapter.

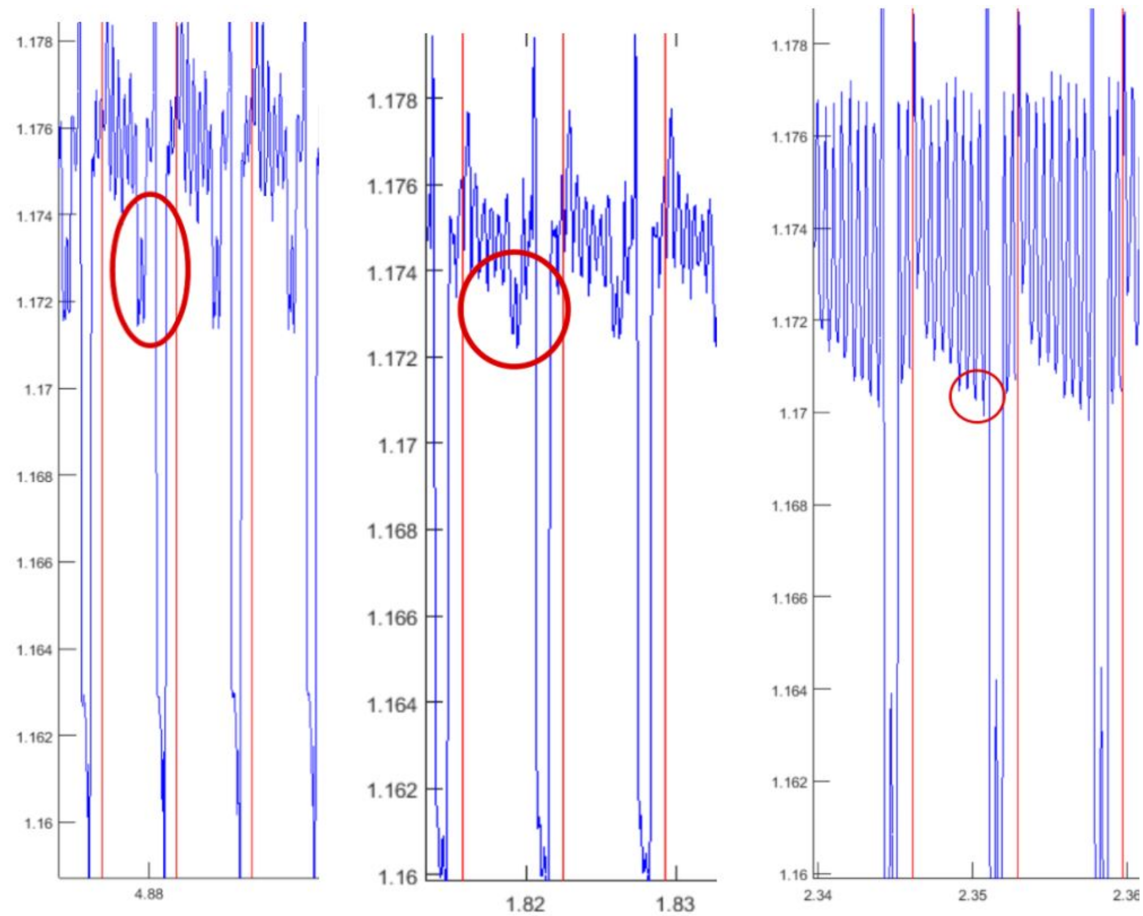


Figure 6.5: The circled dip is what the receiver uses to interpret whether or not a shadow is present, so the longer the dip, easier and more accurate the processing. a) receiver is 8 ft from the transmitter, b) the receiver is 10 ft from the receiver, c) the receiver is 12 ft from the receiver.

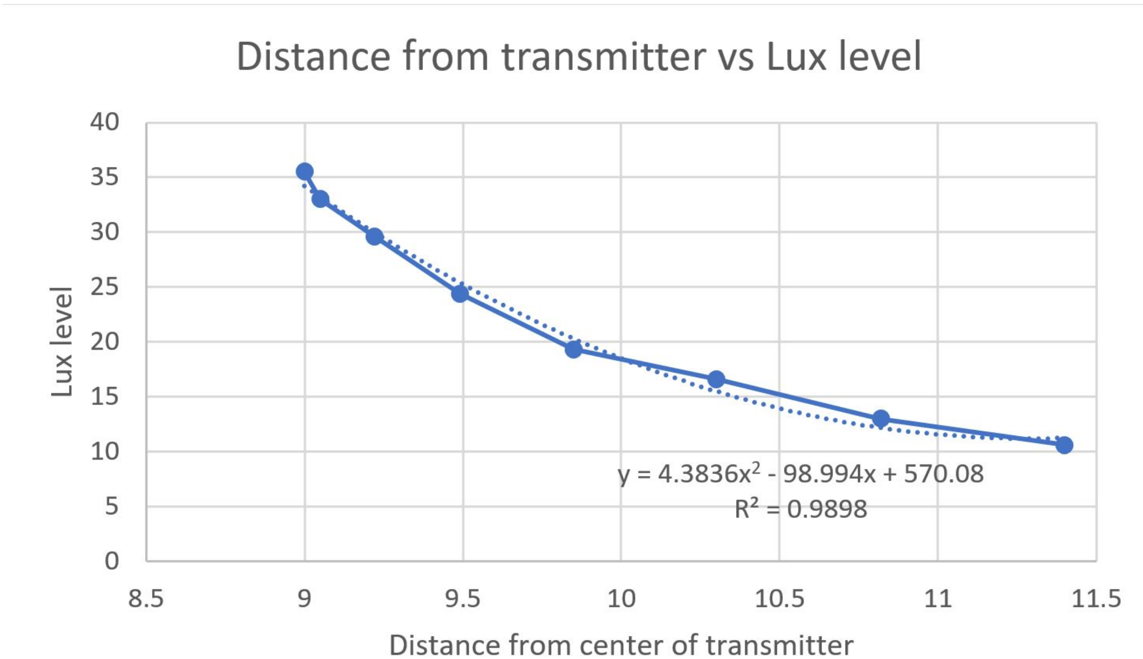


Figure 6.6: The circled dip is what the receiver uses to interpret whether or not a shadow is present, so the longer the dip, easier and more accurate the processing. a) receiver is 8 ft from the transmitter, b) the receiver is 10 ft from the receiver, c) the receiver is 12 ft from the receiver.

Chapter 7

Results and Comparisons

7.1 Introduction

Testing has been done by making people stand in different divisions of the line, running the obtained data through the offline algorithm and estimating which division they were standing on. The conference room where testing is done in is a typical office setting which is 19ftx24 ft. Dense deployment is not required. Only four receivers are used to detect people along a line of 19 ft. Better accuracy and less localization error can be achieved with more receivers. The expected result from the system is the division number the person is standing in for each timestamp from the system.

There are four receivers used to localize people in a line of 19 feet. These receivers have 10 degrees field of vision, so Fig. 7.1 illustrates the areas on the floor it can see.

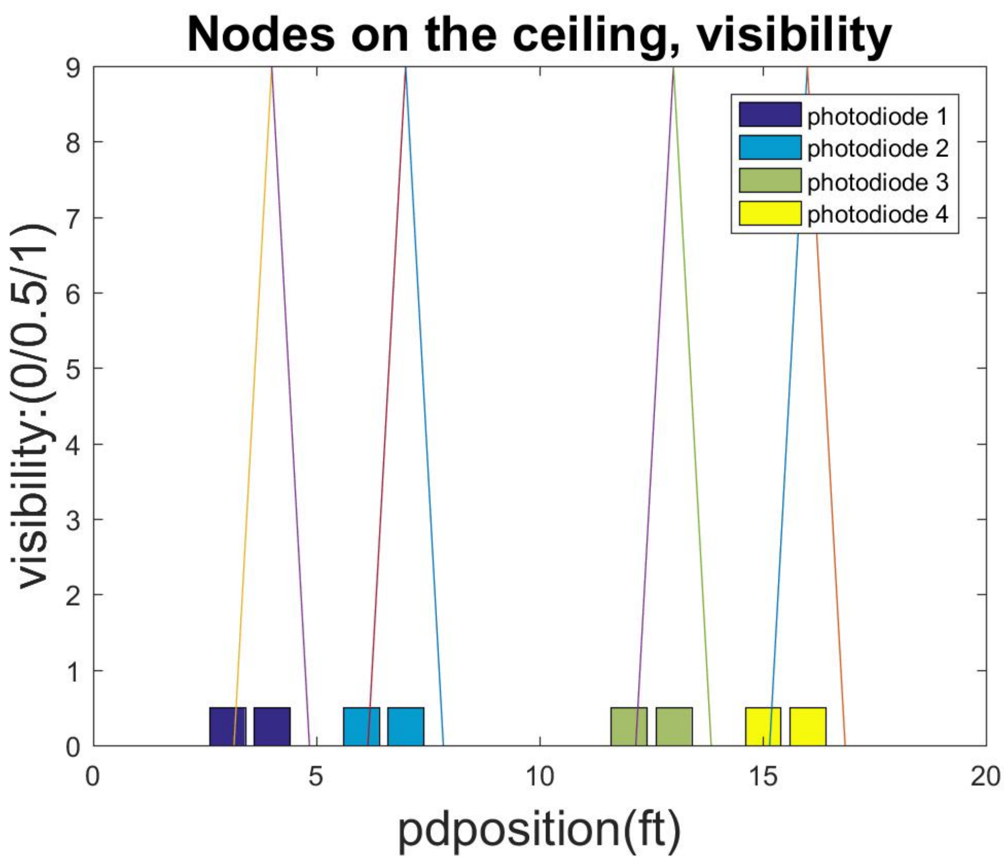


Figure 7.1: Plot showing regions on floor the receivers on the ceiling can see

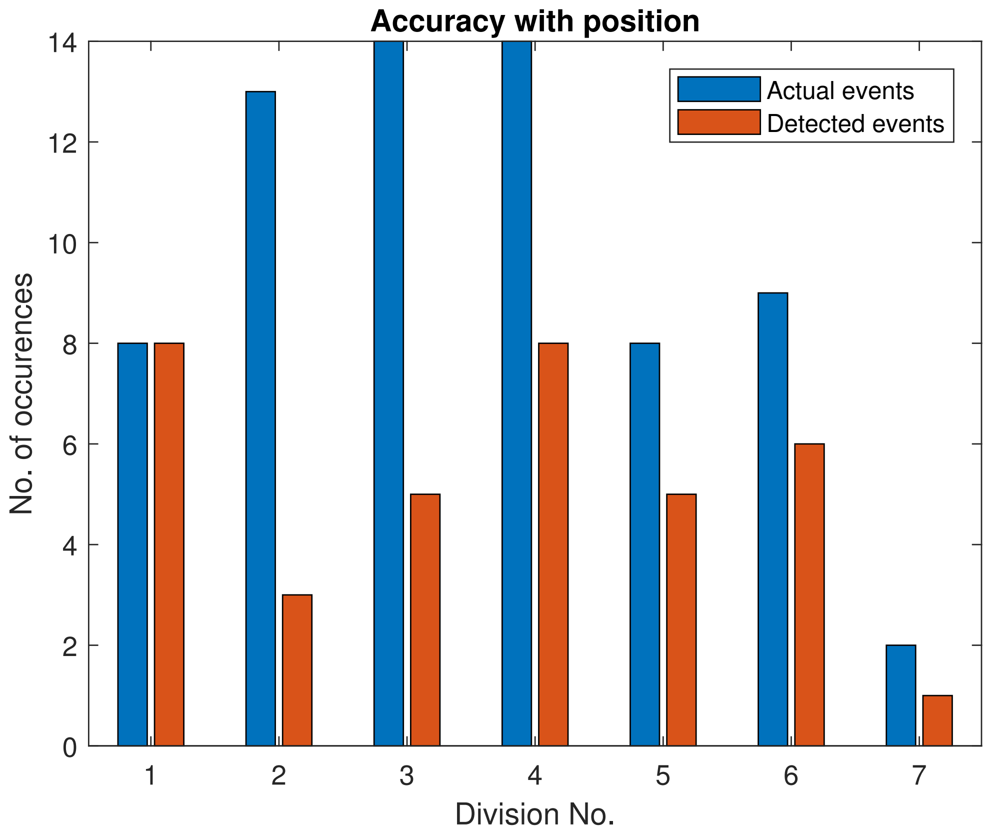


Figure 7.2: No. of occurrences detected by system vs. no. of occurences subject was standing in that division. It can be observed that the accuracy is better at the ends of the line.

7.2 Metrics

Deciding whether the proposed system is suitable or not depends on many factors, especially depending on the application it is needed for, since different situations call for different standards. The following metrics can be used to sufficiently quantify *Eyelight* in localizing humans in a room, as stated by Farid et al. in [1].

7.2.1 Accuracy

The accuracy of the setup is shown using a CDF curve, that shows the probability of error decreasing as localization error increases. Here, the localization error is the distance between the estimated location and the actual location of the person being tracked. There were several observations that were made, such as how the system performed better at the ends of the line as opposed to the center. A possible explanation is the shadow detection of photodiodes even though the person's shadow is not in the region of visibility predicted. It is observed that there is a 95% chance that the person is tracked to an accuracy of 2m.

7.2.2 Responsiveness and Coverage

With the current setup, if the data coming to the server from the node is processed in real-time, it would take less than a second to obtain the location of the person. Once a person stands in a spot, with it taking 32 ms every time the server receives a reading from a particular receiver, the results would be almost instantaneous.

The system consists of individual smart lamps that perform the function of localization when used by itself or with more lamps. The use of more lamps allows the localization range to be extended. For example, using just one lamp relies more on whether the subject is directly under the lamp, while using two allows for shadow manipulation and signatures. Using three in a well-thoughtout configuration makes the range higher, since the three nodes are more spread out and more signatures are possible.

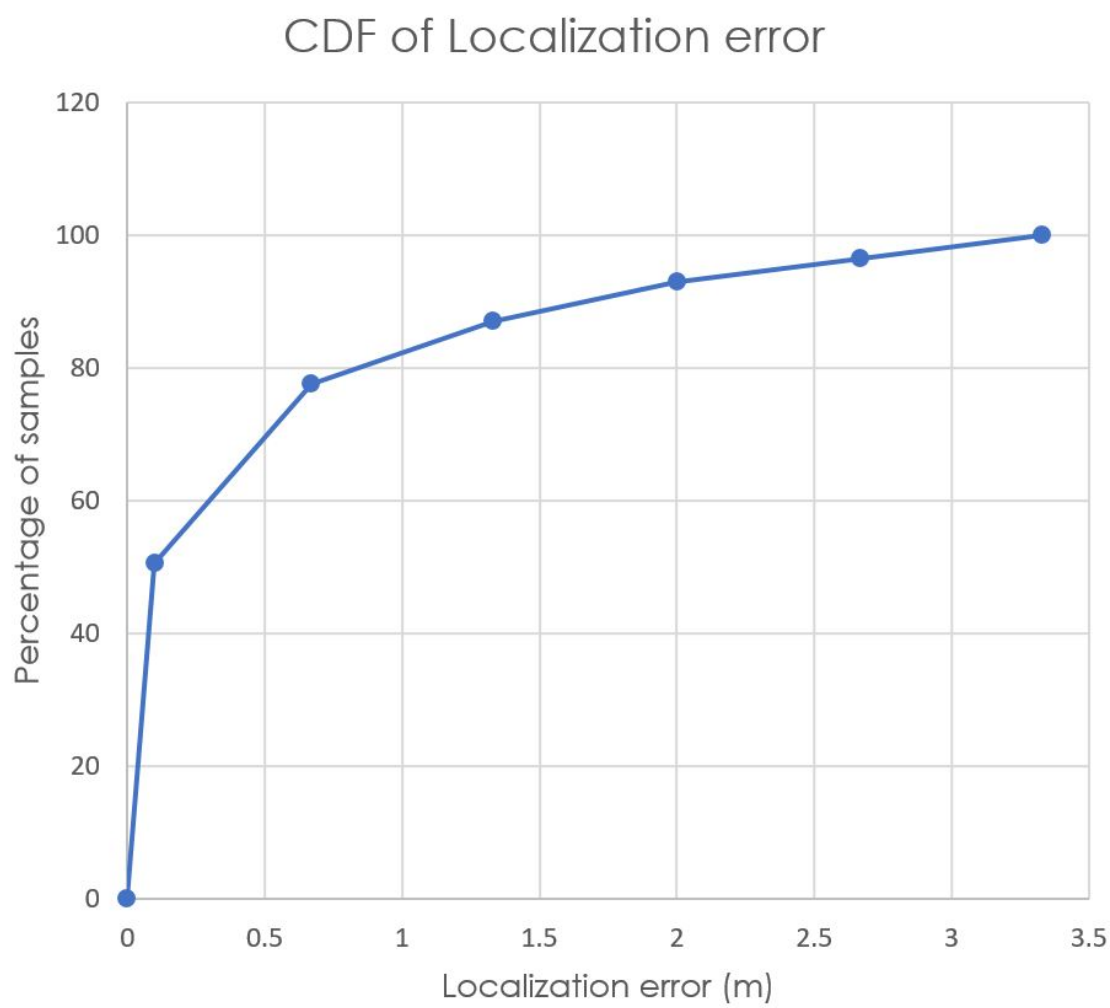


Figure 7.3: Plot showing CDF of localization error.

7.2.3 Adaptiveness and Scalability

In addition to the constant recalibration to get the most updated base signal reading to subtract from the observed signal in order to get the corresponding light level change, *EyeLight* is adaptive in its ceiling-based setup since it has a very low time resolution and only relies on differences in light levels. Even with environmental changes, all of the background is subtracted. In addition, with minor tweaks to the prototype, it can be designed to become a fully functioning regular looking light bulb that can be screwed in. Junwei Zhang's Passive Localizing system using Visible Light first uses the Shine Platform [40] and objects made of mirrors to obtain the accuracy of 5.3 cm. It then uses actual commercial off-the-shelf LEDS and photodiodes and objects resembling the material of construction hats and cars. Since the receiver relies on using reflective light, the objects need to be near the lamps for detection (at around 0.5m below the lamps). This approach may be feasible on a small scale, but for the current scenario of a room and people walking in it, it is not.

As mentioned before, one of the major advantages of this system, and what sets it apart from other existing VLS technology such as LiSense, is its scalability. The system does not need the person to be detected in the range of visibility of the receiver; it is only essential that their shadow is. This reduces the number of nodes required. For a line of 19 feet, only 2 nodes with two photoreceivers are required to localize. Theoretically, according to the 3D algorithm outside the scope of this project, four nodes with four receivers each should be able to localize people inside a 24 ft x 19 ft conference room.

For comparison, Lisense is taken.

LiSense [36] is one of the closest technologies to this project's approach, and from where the idea of using shadows of humans to obtain information about their whereabouts was inspired. As mentioned in the Related Work section, it was developed in 2015 and the setup comprises of several LEDs blinking at different frequencies on the ceiling, and many photodiodes placed on the floor. The aim of this project is to do human skeleton reconstruction using the voltage levels seen at a resistor connected to the photodiode, comparing it to a database which is manually created for different positions. Although this project did not attempt indoor localization, it is notable to include in a comparison due to its similarities. In reconstructing human gestures, its accuracy was 10

There are several drawbacks to this system - to be able to be used for indoor localization it is clear that the number of photodiodes required would increase such that a photodiode is present in every spot possible on the floor. This is a very infeasible method of deploying a setup and the density of sensors is very high.

While the accuracy of localization would theoretically be high, the cost of installation would be much higher than *EyeLight* where only 4 photodiodes are used every 1mx6m. In the *LiSense* 3 meter x 3 meter testbed, 524 photodiodes are used.

For such centimeter precision of accuracy of results, the technology not only depends on a high receiver density, but also on a variety of factors like height and weight of the person, the looseness of clothing they're wearing, etc. Since the average person has a footprint of 1 square foot, such efforts for this particular application are fruitless. Installing so many receivers on the floor may also prove hindering in a practical use case scenario.

7.2.4 Cost and Complexity

As for complexity, while there is one algorithm that needs to be run to determine the best configuration, and two that need to be run to localize the person, these algorithms taken individually are very simple with a run time of 1 second each on a standard 8GB RAM portable laptop, and are a good compromise as opposed to having a learning step.

The cost of the setup of two nodes and four receivers, with the wires, active and passive components, microcontrollers and the server are tabulated in the Node Implementation section. These costs reflect those of the prototype used. Each node prototype has a default of 4 receivers.

Table 7.1: Prototype costs for EyeLight

Name of Component	Cost of one component	No. of Components	Total
Ecosmart 65W BR30 LED bulb	\$3.64	2	\$7.28
Honeywell photodiodes	\$0.75	4	\$3.00
MSP432 with CC2300 Booster Pack	\$13.49	2	\$26.98
Passive components	\$1		\$1
Dell server	\$250	1	\$250

The cost of each node currently comes to around \$25.

7.2.5 Overall Comparison

Compared to the above two methods of Device-free Passive Indoor Localization methods using Visible Light, *EyeLight* truly offers a novel, efficient strategy in terms of accuracy, power requirements and hardware costs in practical scenarios where a person is standing in a conference room with the lamps on a ceiling 9ft high. The number of nodes required is minimal, making it scalable even for the biggest rooms. LED lamps are ubiquitous in modern rooms, so it only makes minor modifications contained to the ceiling. To the knowledge of this project, there are no other technologies that attempt to use Visible Light Sensing to perform Device-free Passive Indoor Localization.

Chapter 8

Conclusions

A novel method of localizing indoors using visible light has been established. The purpose of this thesis was to investigate a ceiling based passive visible light sensing system to detect the positions of people without any learning steps. For this purpose, a prototype with the intention of sensitively detecting the light levels on the floor is designed and constructed as seen in Chapter 5. The concept of localizing using signatures of different positions on the floor is implemented using visible light. To determine the length of the divisions that a person can stand in and be distinguished between, a simulation is done using MATLAB as shown in Chapter 6. The setup is placed on the ceiling and tested. The results show that localization is possible to an accuracy of 2 ft, as shown in the results section, and to a 94% accuracy for $\pm 2m$ positioning. Several metrics are illustrated in section 8.4, and a comparison of *LiSense*, Zhang's system and *EyeLight* is performed in Chapter 8. Eyelight improves on prior work with its low node density, low localization error and low complexity.

Chapter 9

Future Work

Right now, the only output the photodiode gives is whether it can see a shadow or not. The output of the shadow-detection algorithm is either 0 or 1 - shadow absent or shadow present. The lights are set to flicker in a TDMA fashion. If the system was able to return information about which lamp's light caused the shadow it sees, localization can be done more precisely, since more distinct signatures can be obtained on the floor. An algorithm with reduced computational complexity needs to be devised.

A GUI can be made for easily determining where the nodes must be setup to localize depending on the room dimensions.

On the other hand, upon installation, the setup needs to know where the transmitters are in the room and where the receivers are pointed. It needs this data for processing. To be commercialized it will be further convenient for the users if they could merely screw in the setup and have it localize where it is by itself without having to input these value.

A future prospect would be to have the setup work real time, for large rooms. This way action responses can be set. For eg., if a person stands in a particular region of the room the lights in that portion of the room would turn on since the setup detected it in real-time.

Multiple people could be differentiated at the same time.

In households, the node could be plugged into the wall socket and pointed upwards so that the silhouettes fall on the ceiling.

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