DATA FUSION OF AMBIENT TECHNOLOGIES TO EXAMINE RELATIONSHIPS BETWEEN ACTIVITY AND MILD COGNITIVE IMPAIRMENT

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DATA FUSION OF AMBIENT TECHNOLOGIES TO EXAMINE RELATIONSHIPS BETWEEN ACTIVITY AND MILD COGNITIVE IMPAIRMENT

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Being perfect is not about that scoreboard out there. It’s not about winning.

It’s about you and your relationship with yourself, your family and your friends. Being perfect is about being able to look your friends in the eye and know that you didn’t let them down because you told them the truth.

And that truth is you did everything you could.
There wasn’t one more thing you could’ve done.

Can you live in that moment as best you can, with clear eyes, and love in your heart, with joy in your heart?

If you can do that, you’re perfect.

Friday Night Lights

For Donald Edwin Zelko –

until we meet again.

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Now to Him who is able to do exceedingly abundantly above all that we ask or think, according to the power that works in us, to Him be glory in the church by Christ Jesus to all generations, forever and ever. *Soli Deo Gloria*.

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SUMMARY

Mild Cognitive Impairment (MCI) is a disorder that affects millions of elderly individuals across the world. Common symptoms of the condition are decreases in memory function, impaired motor control which can cause regularly occurring states of confusion. Arising from this disorder is the serious concern about how best to support those afflicted by MCI in continuing to live fulfilling, independent lives while protecting them from hazards that may arise from their MCI.

Of particular interest is investigating movement patterns people with MCI exhibit while pertaining tasks or daily routines. Repetitive movement throughout the same areas of a house – such as going from a bathroom, to kitchen, to bedroom in a cyclic fashion – may indicate increasing severity of MCI. Though there is no known cure or prevention for MCI, identifying if one's condition is getting more severe is imperative to improving quality of life for these individuals.

In this thesis, methods of low-cost location tracking were explored. A low-cost location tracking system was created and detailed. The system implemented Bluetooth technologies for identifying individuals. For receivers, devices such as Raspberry Pi computers were used to record movement patterns of individuals as they moved around an environment. Simulated scenarios were developed used to create algorithms to determine someone's location in real time.

CHAPTER 1

INTRODUCTION

1.1 Mild Cognitive Impairment

Mild Cognitive Impairment (MCI) presents as a “syndrome with impairment of memory or [other] cognitive domain that does not interfere substantially with personal autonomy.”[1] and it, “represents the intermediate state of cognitive function between the changes observed in aging and a diagnosis of dementia”.[2] MCI has only recently fallen under scrutiny in the last 30 years and was identified through a myriad of neuropsychological tests such as the Global Deterioration Scale (GDS) saying that if someone with a GDS ranking of 3 were more likely to have a diagnosis of MCI.[3]

Though these explanations for MCI give some insight into what MCI is, there is sufficient ambiguity in its definition to frustrate attempts for its diagnosis. A reason for this was that, until recently, there were thought to be bespoke subtypes of MCI in existence yet this was never actually demonstrated to be true. However, Csukly *et. al.* [4] was able to demonstrably show the differences between two proposed sub-types: amnestic MCI (aMCI) and non-amnestic (naMCI). aMCI suffers had significant decreases in the cortical thickness of the entorhinal cortex, the fusiform gyrus, the precuneus and the isthmus of the cingulate gyrus in comparison to control groups and naMCI sufferers.

Across all types of MCI, the syndrome predominately affects geriatric cohorts; international reports have varied wildly stating that MCI affects only 3% of elderly individuals to over 42% of all elderly across the world.[5]. The number of elderly people in the US is expected to skyrocket from 52 million to 95 million people by 2060.[6] Though it is hard to definitively say how many US elderly individuals are affected by MCI, as the number of elderly increase so will diagnoses of MCI. Further complicating issues, is the fact that there are no treatments approved by the Food and Drug Administration for any type of MCI - this has remained unchanged from the 2005 investigative paper published by Petersen & Morris.[7]

This variation and numerous complications alludes to the biggest problem in treating MCI: diagnosing the syndrome.[8] In a systematic review conducted by Stephan *et. al.* [9] in 2013, it was found that significant discrepancies between approaches to diagnosing MCI of any type. One of their explanations for this is the subjective criterion that can be present in the diagnoses offered by clinicians. This highlights the need for a uniform diagnostic methodology that can exist independently of any clinician.

1.2 Current Diagnostic Approaches

Several researchers have attempted to relate information from wearable devices, ubiquitous computing methods, and traditional clinical observations.[10]–[12] In particular, Kuhlmei *et al* [12] showed that actigraphic measurements collected during the daytime is negatively correlated with memory deficits as assessed by clinical staff using the DemTect battery [13] In this study, the authors examined 76 subjects of which 32 had dementia, 21 MCI, and 23 were held as controls over a period of 5 days and recorded ambulatory activity during the day via the Actiwatch Mini.[14]

Akl *et al* [10] conducted a home-based study using ambient technologies (i.e. passive infrared sensors, wireless contact switches, and motion sensors) and followed 97 neurotypical subjects, who lived by themselves, over the course of three years. Proving the difficulty in this domain, Akl *et al* were only able to use 68 subjects due to data loss and/or corruption. In this sub-group, 15 developed MCI based on in-home assessment from the research team using the Mini-Mental State Examination [15] and the Clinical Dementia Rating system [16]. Using 98 features and a SVM with an RBF classifier trained using a leave-one-out-cross-validation process they were able to successfully identify MCI who had developed MCI in agreement with previous clinical assessment with an AUC of 0.97.

In another similar study, Cook *et al* [11] were able to detect MCI in a cohort of 84 individuals over a period of two years. In the cohort there were 9 subjects who met the criteria for Parkinson's Disease and MCI, 16 with strictly Parkinson's Disease, 9 with MCI, and 50 healthy older adults. The study took place both in the subject's home and in the researcher's CASAS smart home environment [17]. CASAS includes ceiling-mounted infrared sensors, magnetic door sensors placed on cabinets and doors, lighting sensors, temperature sensors, vibration sensors on commonly used objects (such as a broom, medicine dispenser, hand soap dispenser, etc.). Additionally, the researchers had participants strap Android smart phones to their upper arm and an IMU to their ankle. Using 3152 features, Cook *et. al.* used a battery of classification methods: Decision Tree, Naive Bayes, Random Forest, SVM, Ada/DT, and Ada/RF.

They reported a max AUC in differentiating: the control from Parkinson's subjects of 0.84 (0.80 Acc), healthy adult from those with MCI and Parkinson's; Parkinson's only; and MCI 0.97 (0.86 Acc), healthy adult from Parkinson's and no MCI of 0.97 (0.97 Acc), and healthy adult from MCI of 0.96 (0.87 Acc).

1.3 Limitations of Current Work & Motivation of This Proposal

However, a few common issues that arise in these approaches are separating the person of interest from their environment, automating the classification of events, and data reliability. Akl reported that in their study [10], if someone else visited the individual, this could confound the data they collected and would be forced to throw out tremendous amounts of data as they could not separate signals collected from the individual and visitors. They even went on to admit that their high performance was most likely due to overfitting - a common issue with RBF kernel-based SVMs. Cook noted that in their work [11], they had a team of observers who manually recorded at what time and what type of action an individual was taking.

Furthermore, there has been little research done to scale these ambient measurement methodologies. Most pressing of problems found in scaling ambient measurements we propose are:

1. Monitoring daily changes in cognitive behavior based activity
2. Social interaction measurements to determine usage patterns
3. Behavioral response to change in therapies and/or environments

Reinertsen and Clifford [18] wrote a comprehensive review discussing the tremendous utility available in passive monitoring of those suffering from various neuropsychiatric illness (i.e. major depressive disorder (MDD), bipolar disorder (BD), and schizophrenia). From the review, Vancampfort *et. al.* [19] were able to show that those suffering from MDD, BD, or schizophrenia live a dramatically more sedentary lifestyle. Conversely, those experiencing excessive movement may show mania or psychosis which may be an important decision-support factor in a diagnosis of schizophrenia or BD. Furthermore, Saeb *et. al.* [20] in a two week long study with 28 subjects suitable for data analysis, demonstrated that by examining those with a lower location entropy (increased amounts of time spent in few locations) the higher probability it was for a subject to be depressed. The findings enumerated here show that daily monitoring of cognitive behavior via motion and location recording can lead to the detection of possible cognitive changes.

As shown by Çakmak *et. al.* [21], they highlighted a novel development in the effectiveness of creating personalized healthcare models using personal data to determine the potential for adverse health outcomes. Though this approach addressed congestive heart failure (CHF), the symptoms surrounding CHF are very analogous to neuropsychiatric illnesses: decreases in activity and social interaction. It is a well-known fact that social relationships play a significant role in health outcomes [22], [23] and also a sad reality than many elderly individuals lose a majority of those relationships with age [24]. Morris *et. al.* [25] conducted interviews with a cohort of 45 individuals comprised of ten healthy elders, seven with MCI, twenty-five facing dementia, and three family caregivers. From their work, they identified three key “Threats to Social Connectedness” being:

- **Losing Track** - information processing delays due to cognitive impairment make participating in the flow of conversation difficult.
- **Forgetting** - impaired memory makes social network maintenance excessively burdensome.
- **Fears of Imposing** - elders struggling with cognitive decline express reluctance to ”impose” upon others.

Morris *et. al.* [25] found that this led individuals struggling with cognitive decline to withdraw from social events, avoid them entirely, and even stop answering the phone for anxiety of forgetting or not understanding something. The approach proposed by Ã‡akmak *et. al.* [21] to create models based on personal information would be possible only in a situation where copious amounts of time series data for an individual would be present. An answer to finding this data is in the usage of ambient sensing to monitor social interactions. From this analysis we could determine usage patterns in a given space and how cognitively impaired individuals may socialize with others present similar to work done by Terry *et. al.* [26] in the creation of the *Social Net* project.

Subtle changes in the environment can have tremendous impacts on individuals as discussed by behavioral economists Thaler and Sunstein in their book, *Nudge: Improving decisions about health, wealth, and happiness* who introduced the idea of subtly engineering people’s environments to lead to a desired outcome (i.e. *nudging*) [27]. Rashid and Zimring [28] did an empirical literature review which explored indoor environments and the interplay between health and subtle influences that were controlled in them. One ambient control highlighted in the review was lighting. Controlling lighting was shown to possibly shorten hospital stays for BD subjects [29] and may aid sleep quality in the elderly [30]. Using ambient technologies, we could better examine the dynamics of how a user behaves in a specific environment and their relationships with changes in their therapies and/or environment.

Building upon prior research and the unexplored aspects of these research endeavors, we propose to investigate methods for scalable deployments of ambient technologies to monitor daily changes in cognitive behavior, observe social interactions, and catalog behavioral responses to therapy and/or environmental change of individuals diagnosed with MCI. This study would take place in the context of Emory University's Mild Cognitive Impairment Empowerment Program (MCIEP). The MCIEP will give us the ability to follow individuals in simulated at-home environments. Furthermore, MCI persons will engage in communal activities with other MCI-afflicted individuals.

The specific aims of this proposal is to:

1. Design, build and test a wearable device that emits Bluetooth signal
2. Implement a distributed sensor system and software architecture to triangulate position of an individual
3. Assess the spatial resolution of the location system and the accuracy in determining the specific location of an individual

To achieve these aims, we propose the development of a wearable device that emits a Bluetooth signal which is associated with a unique physical address that we can associate with members of this program to provide information on the individuals' movement throughout their daily program activities. Moreover, this wearable will enable other data inputs to be collected, such as actigraphic and geolocation data that will enable us to create a more holistic picture of the individual as they progress with MCI using data fusion and machine learning methods. Using the signal obtained from this device, we will develop a triangulation algorithm which utilizes these distributed sensors to determine the position of this individual in a given environment. Finally, we will assess this methodology in terms of accuracy and resolution (i.e. to what extent can we determine an exact position of individual). We expect this approach to lead to the identification of novel biomarkers present in individuals with MCI that future clinicians can use to aid in the diagnosis and treatment of MCI-afflicted persons.

1.4 Overview of Thesis

This thesis is comprised of the following chapters:

1. **Chapter 2: Background on Location Monitoring** – covers an overview of on common uses for location monitoring in commercial applications. Furthermore included is a summary of common techniques that were considered for exploration in this thesis.

2. **Chapter 3: Hardware Design** – an analysis of current Bluetooth beacons available on the market from which was chosen the beacons used in this thesis. Highlights the set-up that was used for the experiments taken place in this work.

3. **Chapter 4: Location Tracking Algorithms from Bluetooth Sensors** – enumerates three discrete cases from which position tracking algorithms were created. These cases are idealized situations meant to be achievable that could in the future be compiled into a robust solution.

4. **Chapter 5: Conclusion** – a recap on what this thesis offers to the academic community and next steps for future improvement of the system.

CHAPTER 2

BACKGROUND ON LOCATION MONITORING

Monitoring location has had application in a variety of domains ranging from use cases such as commercial asset tracking to surveillance of criminals on probation [31]. Table 2.1 shows a small sample of patents regarding location monitoring and illustrates the amount of different applications are available for generic location tracking technologies.

Title	Description	Year	Ref
Wearable Location Monitoring and Communications System	Device capable of determining individual geographic location to determine entry into permissible/unpermissible regions.	2001	[32]
Asset and Personnel Tagging System Utilizing GPS	A system for tracking tagged objects outdoors.	2004	[33]
Method and System for Asset Tracking	An asset tracking and panic alarm system.	2007	[34]
Asset Tracking with Error Adaptive Boundary	A method for tracking assets from central stations using tracking devices or site identities broadcast from transmitters within a wireless network.	2013	[35]
System and Method for Improving GPS Accuracy in a Device by Utilizing Increased Time Stamp Accuracy	Methodology for updating UTC timestamps within a GPS to improve pseudorange calculation.	2016	[36]

Table 2.1: A brief survey of patents citing usage of location tracking technologies personal and asset monitoring.

Technique	Accuracy (SI)	Limits	Example
Radio time-of-flight lateration	1 - 5m (95 - 99%)	Not for indoor use	GPS
RF Lateration	1 - 3m	Proprietary, 802.11 interference	PinPoint 3D-iD
802.11 RF Scene Analysis & Triangulation	3 - 4.3m (50%)	Wireless NICs required	MSR RADAR
Proximity	$\approx$ 1m	Must know sensor locations	Automatic ID Systems
Scene Analysis, lateration	1mm ($\approx$ 100%)	Control unit tether, precise installation	MotionStar

Table 2.2: An overview of the survey on location determination by *Hightower and Boriello* [37].

In the taxonomy created by *Hightower and Borriello*, they provide a concise overview of techniques in use today for location monitoring [37]. As shown in Table 2.2, several technologies in use vary in accuracy when attempting to determine location. Furthermore, finding a system that can both be accurate while also fitting within the given constraints of an application site is a great challenge. For the purposes of this thesis, the technique of proximity detection was explored using Bluetooth beacons.

CHAPTER 3

HARDWARE DESIGN

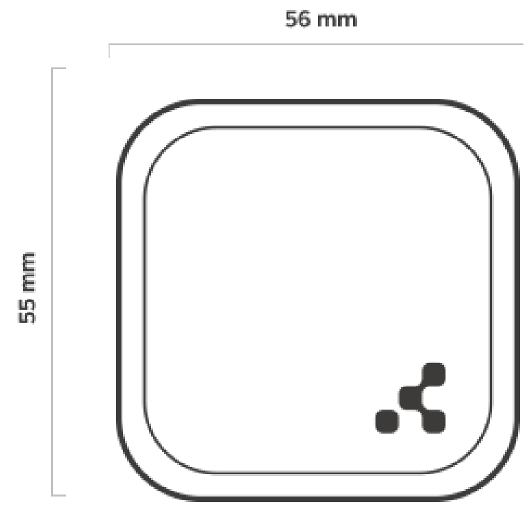
3.1 Overview of BlueTooth Beacon Offerings

Device	Range (SI)	Battery	Company	Cost (USD)	Ref
Smart Beacon SB16-2	$\leq$ 70m	2 - 5 years	Kontakt.io	$22.00	[38]
Proximity Beacons	100m	3 years	Estimote	$25.00	[39]
Series 22 Beacon	$\leq$ 50m	4 years	Gimbal	$45.00	[40]

Table 3.1: A brief survey of Bluetooth beacons available on the market considered for the purposes of this thesis. Such a solution for the system that was developed in this thesis was that the device must be low-cost and have reasonable reach of range. The Smart Beacon SB18-2 was chosen due to its configurable battery life, low-cost relative to other competitors, and flexibility in configuration.

In developing the system used for location tracking, one of the requirements was to equip individuals with Bluetooth beacons. These Bluetooth beacons had to be low-cost while also capable of transmitting a signal an adequate distance in a home environment. Table 3.1 summarizes a brief survey of current market offerings that could meet this need. After comparison and analysis, the Smart Beacon SB16-2 (see Fig. 3.1) created by Kontakt.io due to its low-cost and ease in configuration – both in terms of software and battery.

(a)



(b)

Figure 3.1: Images of the Smart Beacon SB16-2 Bluetooth beacon created by Kontakt.io. (3.1a) Shows what the beacon looks like in deployment scenarios. (3.1b) Gives the discrete dimensions of the device. [38]

3.2 System Set-up

To prototype position tracking, an at-home setting was used that closely matched the eventual environment into which this technology could be deployed. In this at-home setting, nine Raspberry Pi computers (see Fig 3.2) were set-up running a modified Debian Kernel called Raspbian Stretch. [41] These computers were configured as signal receivers that scanned the environment for Bluetooth beacons.

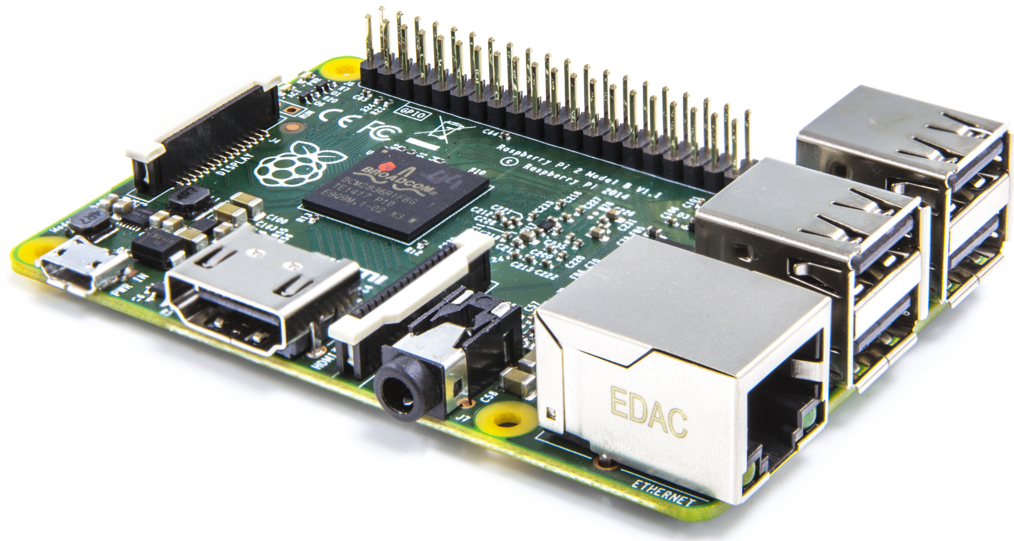


Figure 3.2: A figure of the Raspberry Pi computers used in the set-up for this thesis. These devices cost as much as $10 - 55 USD and are capable of a variety of computational services and prototyping.

Alongside the Bluetooth beacons, accelerometers were attached and paired with them (configuration referred to as a badge). The accelerometer for the badge that was used is the Yost Labs 3-Space$^{\text{TM}}$ Data Logger (see Fig. 3.3) [42] The badge was configured in this fashion to provide an additional data modality for validation of position extraction.

Figure 3.3: The Yost Labs 3-Space™ Sensor Data-logger contains an Attitude and Heading Reference System, Inertial Measurement Unit with an on-board micro-SD card storage and a rechargeable LiPo battery. These features make the device the perfect solution for recording continuous accelerometry data alongside the Bluetooth beacons.

Once the badges were prepared, the Raspberry Pi computers were set-up throughout the home setting. These locations were recorded and mapped to a floor plan of the environment. An individual with the badge then walked throughout the home setting while the receivers were recording Bluetooth signal.

CHAPTER 4

LOCATION TRACKING ALGORITHMS FROM BLUETOOTH SENSORS

Of great significance in developing a Bluetooth based location system is the need for adequate algorithms to extract position from detected signals. Using proximity detection methodologies, Bluetooth signal was captured from the Raspberry Pi receivers. From there, a battery of test cases were developed to develop the appropriate means to detect position via triangulation efforts.

4.1 Location Tracking Algorithm

In order to accurately determine where someone is in an environment, three discrete cases were identified to build an accurate location tracking algorithm utilizing Bluetooth signals. For these cases, we make the base assumption that three receivers are in place and that they receive signal from only one Bluetooth badge beacon moving between these three receivers. Before operating on these cases, it is useful to clarify vocabulary:

- When using the word, *Contiguous* it is meant that a signal is not missing any data points over the period of time the receiver is collecting information.
- When the word *Continuous* is used, it is meant that a given receiver will always have an associated received signal value that does not vary greatly from its previous values.
- In the following cases, *Overlapping* means that a receiver has a received signal strength that creates a perimeter around a receiver that overlaps with other receivers. In this mode of testing, we expect to see unions of three overlapping circles.

Although by themselves, each case is not adequate to address the various complexities that one encounters in real deployment settings. However, using this case-based approach, an algorithm was developed from these simplified cases that was able to better approximate a realistic deployment.

4.1.1 Contiguous & Continuous Overlapping Signals (Case 1)

Assumptions

For Case 1, we make the following assumptions:

1. That the incoming signal is continuous and contiguous.
2. All three perimeters surrounding a receiver *always* overlap.
3. The location of the person holding a badge is considered to be the centroid of the union (or polygon) formed by the three overlapping perimeters.

Starting from these assumptions, a graphical representation was generated to visualize the placement of receivers. Fig. 4.1 displays the theoretical set-up of Case 1 and the assumed position of an individual passing in proximity to the receivers (demarcated as the black point in the center of the overlap generated by the circles).

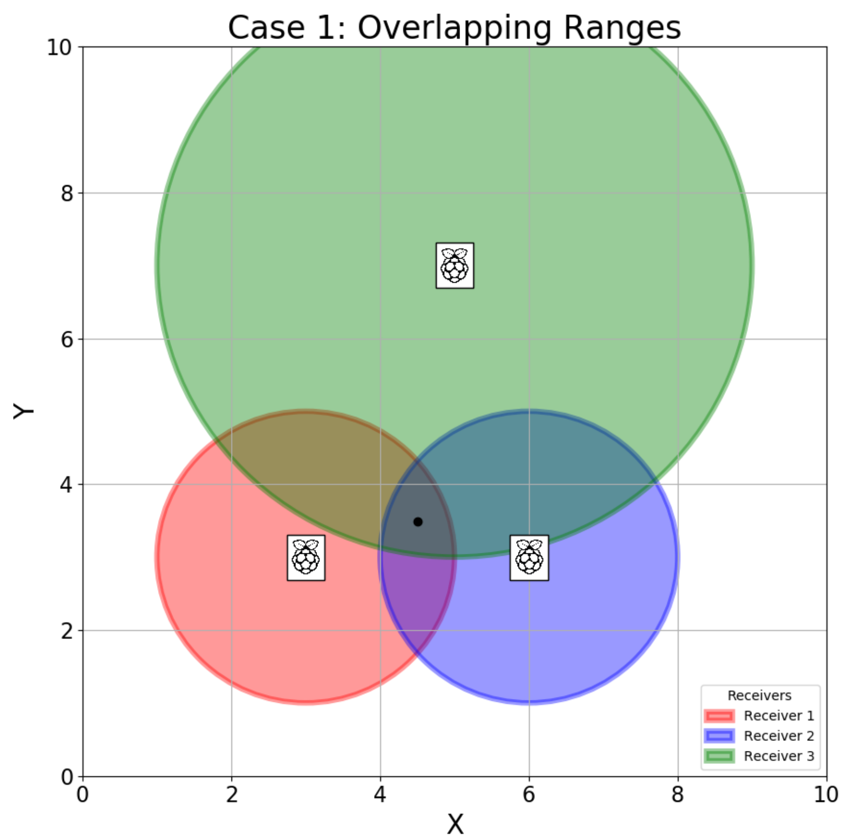


Figure 4.1: Each receiver, symbolized by the icon for the Raspberry Pi computer, is centered in each perimeter generated by a received signal from a badge passing in proximity to the receivers. The assumed position of an individual is symbolized as the black point in the center of the overlap created by the overlapping ranges of the receivers.

Algorithm

An algorithm was developed for Case 1 (see Fig. 4.2 for a pictorial summary):

1. Receivers were fixed at particular points along the Cartesian plane. Each receiver was given an associated radius to ensure overlap.

2. The intersecting points between circles were determined using the following approach [43]:

   (a) Let $Circle_1$ and $Circle_2$ be centered at the points (a, b) and (c, d) respectively.

Furthermore, let $Circle_1$ and $Circle_2$ have r_1 and r_2 as their respective radii.

(b) Using the midpoint formula, a formulation for the distance between two circles can be generated as follows:

$$D = \sqrt{(c-a)^2 + (d-b)^2} \tag{4.1}$$

(c) Next, using Heron's formula, a formulation for the area of the triangle formed between overlapping circles can be found:

$$A = \frac{1}{4}\sqrt{(D+r_1+r_2)(-D+r_1+r_2)(D-r_1+r_2)(D+r_1-r_2)} \tag{4.2}$$

(d) Let P_1 and P_2 be the intersection points at (x_1, y_2) and (x_2, y_2) respectively. Combining equations 4.1 and 4.2 together, one can develop the equations for the intersecting points of two circles as follows:

$$x_{1,2} = \frac{a+c}{2} + \frac{(c-a)(r_1^2 - r_2^2)}{2D^2} \pm 2\frac{b-d}{D^2}A \tag{4.3}$$

$$y_{1,2} = \frac{b+d}{2} + \frac{(d-b)(r_1^2 - r_2^2)}{2D^2} \mp 2\frac{a-c}{D^2}A \tag{4.4}$$

3. Let circle C be centered at (x_1, y_1) with radius r and let the ordered pair (x_2, y_2) represent a point, P, of interest. Using an iterative process and the Pythagorean Theorem, the intersecting points that formed the overlapping area were determined with the following logic:

(a) If the following statement,

$$(x_1 - x_2)^2 + (y_1 - y_2)^2 < (r)^2 \tag{4.5}$$

is true, then P falls within C.

(b) If the following statement,

$$(x_1 - x_2)^2 + (y_1 - y_2)^2 = (r)^2 \tag{4.6}$$

is true, then P falls on the circumference of C.

(c) Otherwise, if the following statement,

$$(x_1 - x_2)^2 + (y_1 - y_2)^2 > (r)^2 \tag{4.7}$$

is true, P is not contained within C.

4. Finally, once the intersecting points that lie on the overlapping region and overlap with all circles are discovered, a simple arithmetic mean is calculated across these points' x and y coordinates to determine the center of the overlapping region.

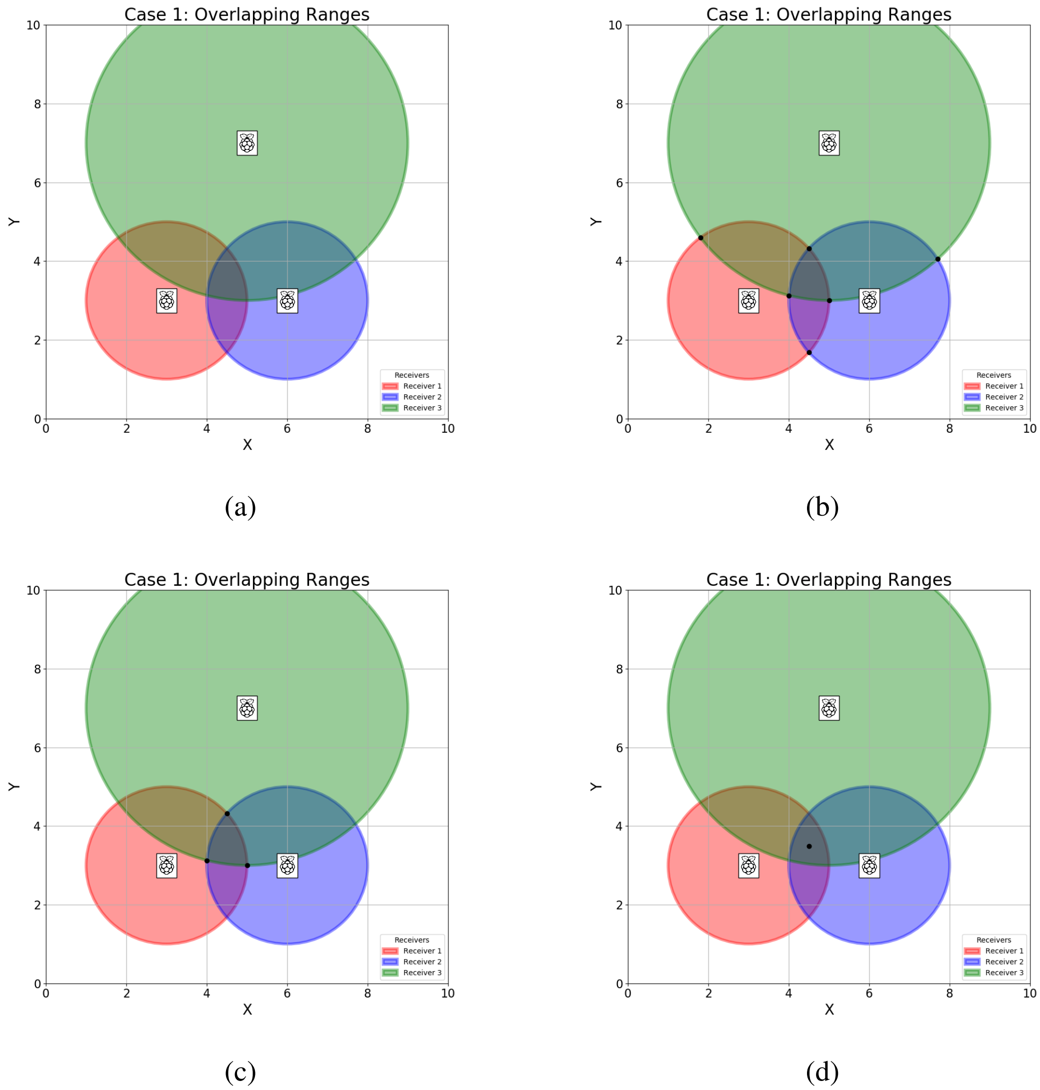


Figure 4.2: This figure pictorially summarizes the algorithm developed for Case 1. (4.2a) Depicts the theoretical set-up based on Case 1. (4.2b) Extracts all the points of overlap that exist between the circles. (4.2c) From the overlapping points that were extracted, the points that overlap between all three circles (which also form the overlapping section) were identified. (4.2d) Finally, a simple average was take across the points that overlap in the union to extract the centroid of the overlapping region.

4.1.2 Contiguous and Continuous Non-Overlapping Signals (Case 2)

Assumptions

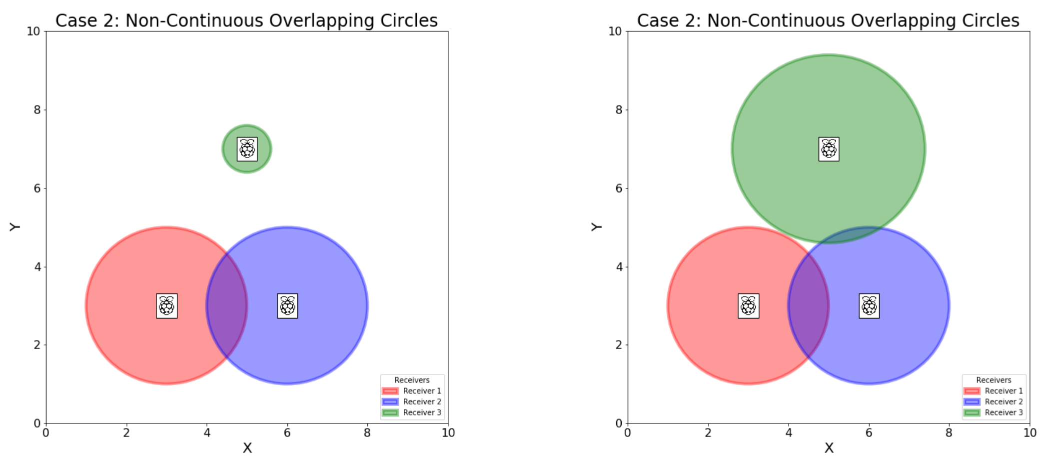
For Case 2, the following assumptions are made

1. That the incoming signal is continuous and contiguous.

2. All three perimeters surrounding a receiver *do not always* overlap.

3. The location of the person holding a badge is considered to be the centroid of the union (or polygon) formed by the three overlapping perimeters.

Unlike Fig. 4.2a, all the perimeters are not initialized to overlap in Case 2. Furthermore, Case 2 actually presents with two sub-cases that needed to be solved that is best illustrated in Fig. 4.3.



(a) (b)

Figure 4.3: These are the two distinct sub-cases that were evaluated in order to solve Case 2. (4.3a) Shows the situation where two circles do overlap and form a distinct overlapping section. However, it does not take into account Receiver 3 which has a perimeter outside of the overlap. (4.3b) Illustrates when Receiver 3 does start overlapping with the other receivers present but does not form a overlapping section between the three receivers.

Algorithm

To not only solve Case 2 but also the two sub-cases, the following algorithm was created based on the algorithm used in Case 1:

1. Receivers were fixed at particular points along the Cartesian plane. Two receivers

were given an associated radii that overlap between themselves. One receiver was given a radius that did not overlap or intersect with the perimeters of the other circles.

2. To determine the receiver whose perimeter does not overlap with the other receivers, the following sub-routine was formulated (illustrated in Fig. 4.4):

   (a) Equations 4.3 and 4.4 were used to determine which points overlap to form the overlapping section between the two receivers whose perimeters do overlap.

   (b) Reasoning inductively, the number of circles that form a shared overlapping region is the same number of intersecting points that are shared between all circles in this overlapping region. If the number of receivers present in a given scenario are not congruent to the number of intersecting points in an overlap, then one can know that a receiver is being left out of this overlapping region.

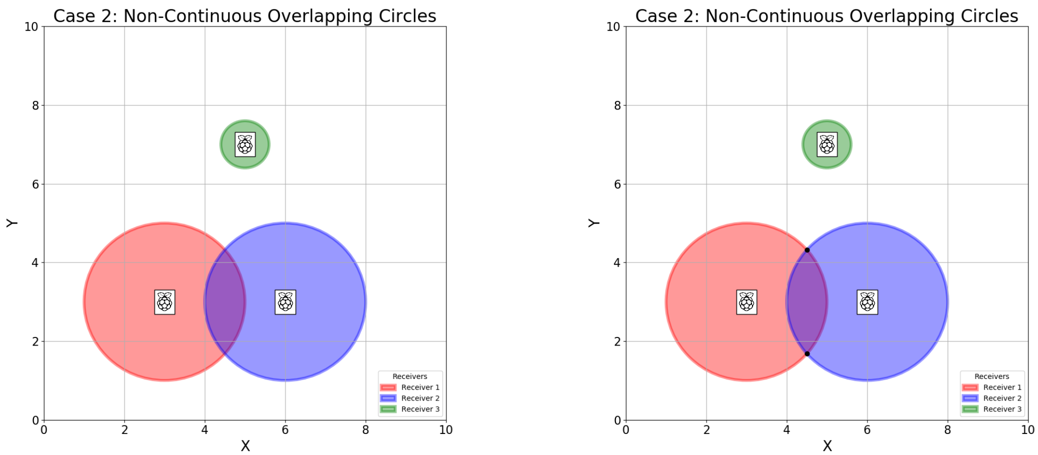
   (c) An iterative process is then applied to determine the missing receiver by testing the points calculated in (a) via the logical statements defined in statements 4.5, 4.6, and 4.7. If a receiver does not contain within its perimeter none of the previously determined intersecting points, then that receiver is the receiver which does not overlap with the other two receivers present.

3. Once the non-overlapping receiver is identified, the radius of that receiver is iteratively boosted using a greedy process to force all three receivers' perimeters to overlap (this iterative process is demonstrated in Fig. 4.5).

4. After all receivers are made to overlap, the remainder of this algorithm follows each step enumerated in Case 1's algorithm.

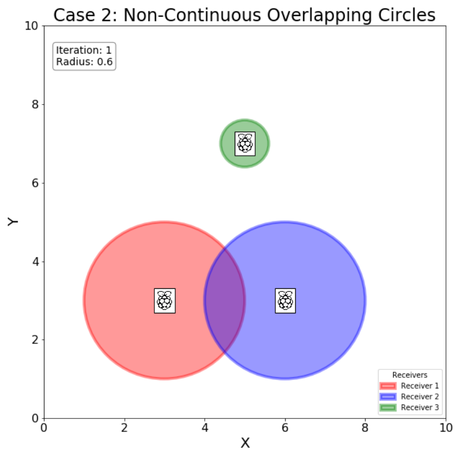
The greedy process detailed in step 3 can be a point of computational inefficiency as it does not guarantee the best solution. One can gain better resolution when forcing an overlap by choosing a smaller interval by which to increase the radius of the receiver's perimeter. However, this comes at the cost of more computational steps to achieve overlap.

Inversely, one can increase the step size by which to increase the radius of this receiver to force an overlap. Though this decreases the number of computational iterations to gain an overlap, the trade off is a less accurate overlap.

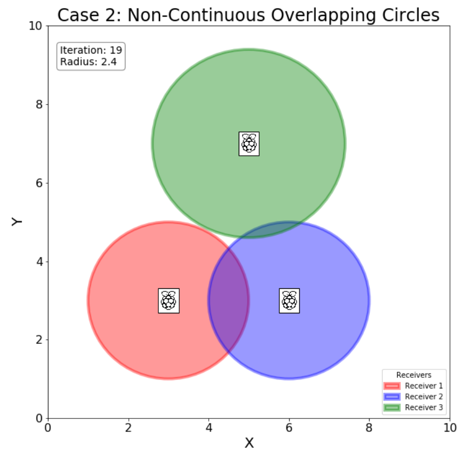


(a) (b)

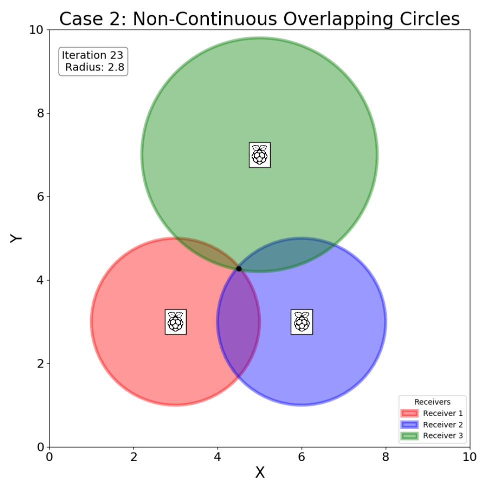
Figure 4.4: Determining a receiver that does not overlap is an imperative sub-routine to Case 2's algorithm. (4.4a) Shows the idealized set-up for investigating Case 2. (4.4b) Demonstrates finding the intersection points between the receiver perimeters that do overlap. The number of points calculated aids in determining if all receiver perimeters overlap.



(a)



(b)



(c)

Figure 4.5: The key subroutine to extracting position in Case 2 is the greedy sub-routine illustrated here. (4.5a) Initializes where the Receiver 3 has been identified as the non-overlapping receiver. (4.5b) Shows the 19$^{\text{th}}$ iteration of the greedy algorithm and the increasing radius of Receiver 3. (4.5c) Shows the terminating iteration of the greedy algorithm that finds a overlapping union of the three and then proceeds to extract the centroid of the overlapping region.

4.1.3 Non-Contiguous and Non-Continuous Overlapping Signals (Case 3)

Assumptions

For Case 3, the following assumptions are made:

1. The incoming signal is non-contiguous.
2. The incoming signal is non-continuous.
3. All three perimeters surrounding a receiver *do not always* overlap.
4. The location of the person holding a badge is considered to be the centroid of the union (or polygon) formed by three overlapping perimeters.

This case is very similar to Case 2 – the only difference being that a signal is not constantly being received by the receivers though a person with a badge is present. This could be due to an error in the badge, an error with the receivers, or the badge is obfuscated by an object in a person's environment.

Algorithm

To evaluate Case 3, the algorithm from Case 2 is used with very minor modifications. The key changes to this version of the algorithm is listed here:

1. Prior to starting this algorithm, a filter must be chosen for smoothing missing data. In this case, one can use a moving average filter such as a median filter to interpolate and smooth missing values. [44]
2. Once a filter is selected, missing data can be interpolated to create a contiguous signal.
3. As the missing data may continue non-overlapping regions, the algorithm created for Case 2 can then be used to ensure continuously overlapping regions.

One of the weaknesses of this algorithm is the initial filter. Depending on the initial data points collected, the filter may demonstrate poor accuracy when smoothing (such as in the case of moving average filters). Furthermore, if there is significant data loss, this could also result in bad smoothing not representative of actual movement patterns.

4.2 Conclusions

The assumptions that were made in the development of a Bluetooth based location tracking algorithm provide a basic foundation for improved location tracking. These assumptions created idealized solutions in which extracting location was achievable. The resulting location that was extracted in these cases was assumed to be the definite center of the overlapping region between receivers.

Utilizing this foundation, one can evaluate additional cases to extract position. Through the evaluation of additional cases, such as forcing overlap between more than 3 overlapping receivers or how to handle when more than one receiver is not overlapping, better accuracy can be obtained in position extraction. This would then result in a contiguous and continuous signal collected from a robust system that enables a high degree of accuracy when reporting the exact location of an individual.

CHAPTER 5
CONCLUSION

In this thesis was demonstrated the foundational means of creating a low-cost position tracking system for its application in the lives of individuals afflicted with MCI. Utilizing Raspberry Pi computers as Bluetooth signal receivers, one can inexpensively set-up a position tracking system in a home based environment. Then, by using the algorithms that were developed in the body of this work, one can then begin the process of extracting a continuous stream of positions from the receivers' recorded signals in real-time.

In this work, many assumptions were made to simplify solving the problem of real-time location tracking via Bluetooth technologies. One simplification was the decision to limit the calculations to 3 receivers. In this idealized set-up, the implicit assumptions was that each of these receivers were perfectly operational and there were no hardware malfunctions. In practice, to track position through an entire building, multiple receivers will have to be used and maintained. Moreover, these receivers may overlap and form regions between more than 3 receivers.

Another assumption is that the receivers are placed exactly as recorded when they are first installed and are not moved while collecting data. An example is of an at home layout as shown in Fig. 5.1. Here, it is known where each receiver is placed exactly making creating an updating map of the environment straightforward. However, if these receivers are possibly bumped by individuals walking around a given space or somehow moved, it can invalidate all data collected from that receiver. Determining how to either account for position shifts or recover flawed data is imperative to future development of systems implementing these technologies.

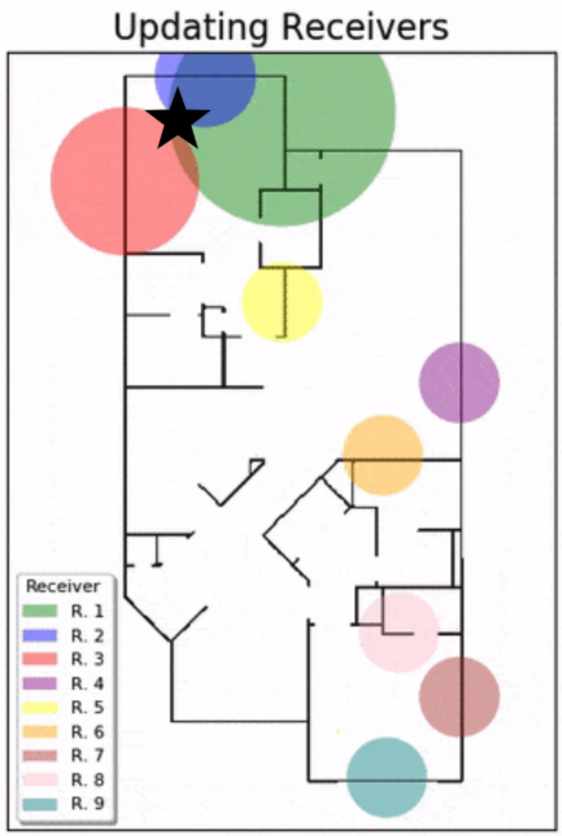


Figure 5.1: This demonstrates a possible visualization scheme where receiver locations are known in an at home setting. Each differently colored bubble represents a different receiver and their position on this apartment layout. The differing radii represent the strength of the received signal detected from a Bluetooth beacon. Receivers 1, 2, 3 have different radii from the other receivers present because they are actively detecting a Bluetooth beacon (the other beacons are held at a base radii when the receivers are first initialized). The star represented depicts the extracted location of someone in that corresponding room following usage of a greedy algorithm.

One facet of future work will be exploring visually this data in a real time manner. The need for this is predicated by enabling caretakers of those with MCI to determine where a MCI person is located in a given environment. Alerts to caretakers can be delivered visually denoting if a MCI person has entered or left a specific vicinity in which their safety may be jeopardized.

Finally, one can utilize data fusion to repair and/or verify positions extracted from detected Bluetooth signals. Using the accelerometry data collected alongside the Bluetooth beacons, advanced filtering techniques such as implementing a Kalman filter, can be utilized to marry these two signals together. [45] One could then create a routine to see if movement is being recorded from the accelerometer to determine if a position pattern suggesting movement is valid.

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