Mobile Accessibility Tools for the Visually Impaired

by

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Abstract

Visually impaired individuals are a growing segment of our population. However, social constructs are not always designed with this group of people in mind, making the development of better electronic accessibility tools essential in order to fulfill their daily needs. Traditionally, such assistive tools came in the form of expensive, specialized and at times heavy devices which visually impaired individuals had to independently look after and carry around. The past few years have witnessed an exponential growth in the computing capabilities and onboard sensing capabilities of mobile phones making them an ideal candidate for building powerful and diverse applications. We believe that the mobile phone can help concentrate the main functions of all the various specialized assistive devices into one, by enabling the rapid and cheap development of simple and ubiquitous assistive applications. The current thesis describes the design, implementation, evaluation and user-study based analysis of four different mobile applications, each one of which helps visually impaired people overcome an everyday accessibility barrier.

Our first system is a simple to operate mobile navigational guide that can help its visually impaired users repeat paths that were already walked once in any indoor environment. The system permits the user to construct a virtual topological map across points of interest within a building by recording the user's trajectory and walking speed using Wi-Fi and accelerometer readings. The user can subsequently use the map to navigate previously traveled routes without any sighted assistance. Our second system, Mobile Brailler, presents several prototype methods of text entry on a modern touch screen mobile phone that are based on the Braille alphabet and thus are convenient for visually impaired users. Our third system enables visually impaired users to leverage the camera of a mobile device to accurately recognize currency bills even if the images

are partially or highly distorted. The final system enables visually impaired users to determine whether a pair of clothes, in this case of a tie and a shirt, can be worn together or not, based on the current social norms of color-matching.

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Chapter 1

Introduction

Much of our social infrastructure is organized with the premise that all members of society have their full vision. Most countries maintain costly transportation systems which rely mainly, if not exclusively, on the ability of sighted car owners to drive through an elaborate road network, whilst urban and rural regions alike are kept adequately lit all throughout the night for the sole benefit of sighted inhabitants. Given these organizational and financial priorities, the needs of visually impaired citizens are at times not addressed adequately, a fact which creates several challenges which visually impaired individuals have to deal with on a daily basis. However, some of the obstacles encountered by visually impaired people can potentially be overcome through simple and cheap assistive software which runs on modern mobile phones. In this thesis, we outline four such mobile accessibility systems that address essential and practical needs of visually impaired users: (a) A mobile navigational tool which provides visually impaired users with directions in unknown indoor environments, (b) A mobile Brailler application for visually impaired users to enter text on touch screens, (c) A system for recognizing currency bills using mobile phone cameras and (d) A system which can determine which clothes could be worn together by using the mobile phone's camera. In this work, we describe the design, implementation and evaluation of the above systems. We have evaluated two of these systems with visually impaired users and describe the qualitative and quantitative enhancements of our solutions through detailed user studies. The underlying theme across all these systems is how to design appropriate smart phone

based applications which take advantage of the rich array of sensors available on such modern mobile phones in order to aid visually impaired users to perform such day-to-day tasks.

1.1 Motivation

> "There was a time when disabled people had no choice but to ask for help - to rely on the 'kindness of strangers.' It was thought to be their lot," [37].

Visually impaired individuals traditionally relied on the assistance and good will of others for their everyday needs. This was due to the lack of basic accessibility affordances when carrying out many daily life activities. Travelling alone was hard or even dangerous due to the lack of carefully constructed sidewalks, or due to the inaccessibility of public transport, which lacked any form of audio announcements [6]. This fact made venturing outside one's familiar place of living to be only undertaken by the truly adventurous of visually impaired individuals. Meanwhile, finding one's way in unknown buildings was impossible due to the lack of Braille signage on building doors and elevators, in addition to the deficiencies present in safety regulations. This further exacerbated the mobility difficulties experienced by such individuals solidifying their social isolation. Any written form of communication was off-limits to blind individuals and barely usable by partially sighted people, a fact which was detrimental to the education of this segment of the population. This situation, coupled with a negative social perception about the abilities of visually impaired individuals, ensured that such persons were more often than not confined to specialized educational or habitational institutions [73]. The employment market was especially hostile to such individuals, who were encouraged not to seek employment in the open market but were protected and nurtured under the auspices of a philanthropic model of social welfare [44].

In recent decades, social and legal developments have enabled the visually impaired to demand a more equal position in modern society [84]. Technological improvements have given more independence to the visually impaired population, overcoming the barriers preventing access to written text and opening new horizons for enjoyable employment. Electronic devices and especially personal computers and mobile phones have become carriers of assistive software, enabling visually impaired users to obtain written material freely, communicate more easily

with the world outside their own community and perform their job duties effectively [24]. Mobile phones with powerful processors have become ubiquitous, displacing previous specialized devices. The rise of the World-Wide Web has especially boosted the access of its visually impaired users to information which was previously available in print and only via the assistance of sighted human readers. Furthermore, the widespread availability of free mapping services has enabled the population of visually impaired people to locate and even explore places of interest before actually visiting them, removing some of the obstacles to unhindered mobility.

However, even today and after years of progress, the interior of an unfamiliar building seems like a labyrinth to some visually impaired individuals, who still have to rely on sighted guides in order to locate a specific room. According to the lawsuit filed by a blind advocate organization [37], American currency is still inaccessible to blind people as all dollar bills have the same shape and lack any tactile markings, making daily transactions inconvenient and even risky. While getting dressed, visually impaired individuals still face dilemmas on what set of clothes to wear together, since determining which of their clothes match still requires the skillful and flawless organization of their wardrobe. Finally, even though the mobile phone has provided many advantages to the visually impaired population, fulfilling their mobility and communication needs successfully, the arrival of touch screen phones has created new accessibility challenges, especially in the realm of text-entry. Given that texting is a ubiquitous form of communication, any such difficulties in entering text on touch screen devices can negatively affect the quality of social interactions enjoyed by visually impaired individuals. This thesis attempts to provide an answer to the above four accessibility challenges by designing and subsequently testing four separate software solutions that can run on a mobile phone. These solutions can help a visually impaired person navigate in an unknown building, recognize American currency, identify if pairs of shirts and ties can be worn together and enter text on a touch screen phone.

1.1.1 The Population of Visually Impaired Individuals and Their Daily Needs

Currently, 2.5 million individuals in the United States are blind or partially sighted [20], which means that they have an optical acuity of 10% even with corrective lenses. However, with the

aging of the population, blindness is becoming more and more prevalent [5]. As reported by the Center for Disease Control and Prevention [20], in the United States "Nineteen percent of persons 70 years of age and older had visual impairments". In today's uncertain global financial climate, this aging of the population of visually impaired users could presumably reduce the availability of meaningful accommodations. As such senior citizens are not always viewed by everyone as able and productive members of society, the quantity of employment opportunities and recreational outlets could also suffer. Regrettably, this assumption is confirmed by the U.S. National Center for Policy Research for Women and Families [20], which states that "Poverty is a fact of life for many blind adults, especially older women," and "Few blind adults receive welfare". In fact, visually impaired individuals of all ages are at a disadvantage, given that "Nearly one in five [of blind individuals] lives in poverty," and "Only 19 percent are currently employed" [20].

With such a devastating rate of unemployment and the social repercussions that it entails, large groups of visually impaired individuals might begin to feel negative self esteem [83], preferring not to leave the security of their home. This in turn could affect the level of social independence that such individuals may attain, a fact which can negatively impact the development of their interpersonal and practical skills. Any deficiencies in a person's essential skills set may in its turn result in an even more reduced self esteem. Fortunately, as put forward by works like the current thesis, software-based assistive solutions may provide such individuals the social and vocational independence they seek, breaking this vicious circle.

Personally, after interacting with many visually impaired people throughout my life, I have come to believe that removing only a few everyday accessibility obstacles would go a long way in drastically altering the social landscape in their favor. These obstacles could be grouped into three large categories. Firstly, the ability to move around without any assistance is the top desire of visually impaired people, especially being able to easily travel around their local town or to find their way in unfamiliar buildings. Fulfilling this need adequately would help them progress enormously on the road to independence. Their second most important concern is access to written text including reading road and building signs, reading mail and completing important documents, such as tax forms. Finally, handling daily tasks, such as effective house cleaning, cooking and separating clothes for laundry/dressing, is also deemed important. At least in the realm of employment, these observations are corroborated by a 1999 survey of 176

visually impaired and low vision individuals which reported that "employment barriers included attitudes of employers and the general public; transportation problems; and lack of access to print, adaptive equipment, and accommodations" [13].

1.1.2 A Barrage of Incompatible and Expensive Specialized Gadgets

Each technological solution to a blindness-related problem traditionally came in the form of a specialized device. For example, the Eureka A4 was one of the first portable personal computers for the blind [25]. This device offered features such as note-taking and music composition, among many others, and it was released in 1986. The relatively small market for assistive technologies, however, meant that few companies would develop for this audience making products very expensive and creating monopolies. For example, Eureka A4's price was around $2500, whilst even today a specialized printer for embossing Braille may cost upwards of $4000 [34]. Meanwhile, these devices were generally not programmable and thus could not serve as a platform on which independent software developers could thrive. In order to reduce costs, manufacturers of such specialized devices may remove user interface components which are necessary for these devices to be used by fully sighted individuals. For example, the Eureka A4 came with no screen and with only a Braille keyboard built-in. This may deny blind individuals the ability to ask for help with their specialized device from a sighted friend, whilst it would be unlikely to find technical support or servicing from anywhere other than the original manufacturer. This unfamiliarity of the general public with specialized devices did not only mean increased costs for the visually impaired user if the device was ever to need repair, but it could also create negative social connotations. Such negative perceptions could develop especially among the social circles of young users, since many of these specialized devices were bulky and lacked any aesthetic appeal. On the other hand, the cost of incorporating extra assistive features into mainstream products was high due to the increased cost of electronics design and production. Blind users were viewed as a special group which was hard to accommodate, was little understood and was thus not seen as a potential customer. Giving access to mainstream technology as a form of legal requirement or social responsibility was not in any way mandated and was thus readily ignored. There was also little market pressure to change this.

During the 90s, a strong push for building accessibility aids on mainstream personal computers was undertaken. This effort has been successful in creating much widespread assistive software, the most important of which is the screen reader. Such software, by allowing speech and Braille access to the computer's screen, has been extremely successful in work rehabilitation, [22]. However, such software is still expensive and may cost more than $1000, [22]. Also, it is not portable and thus cannot solve all the problems of accessing printed text.

More recently, the mobile phone is emerging as a rich unifying platform for assistive software development. Legal requirements and increased awareness concerning the blind population made manufacturers of mobile phones [33] start to incorporate accessibility into their devices. Third party developers [15] stepped-in in order to fill the accessibility gaps of the remaining smart phone platforms. The arrival of cheap smart phones with a high-resolution camera, an array of other sensors and text-to-speech enables accessibility solutions to move away from specialized hardware. Rich programmability allows cheaper development, faster updates and thus the involvement of smaller software players in the accessibility space.

Despite the above advances, assistive or even accessible mobile phone software development is still a nascent market. Consequently, visually impaired users face some challenges when operating their mobile phones. Partially sighted users, for example, may complain about the size of the letters on the relatively small phone screens, whilst blind users have difficulties finding items easily on touch screen phones. These challenges, however, do not seem to be an impediment to mobile phone adoption by the visually impaired. In fact, "people with disabilities continue to choose commodity phones, even when they are aware of specialized access options", [39]. This work uses the smart phone as a platform for consolidating and experimenting with a set of assistive aids.

1.2 Thesis Contributions

This thesis describes the design, implementation, evaluation and user-study based analysis of four different mobile accessibility applications which are summarized next:

1. **Mobile Software for Independent Way-Finding in Indoor Places:** Visually impaired people have a harder time remembering their way around complex unfamiliar build-

ings, whilst obtaining the help of a sighted guide is not always possible or desirable. By sensing the users location and motion, however, mobile phone software can provide navigational assistance in such situations, obviating the need of human guides. We present a simple to operate mobile navigational guide that uses Wi-Fi and accelerometer sensors to help the user repeat paths that were already walked once. The system constructs a topological map across points of interest within a building based on correlating the users walking patterns and turns with the Wi-Fi and accelerometer readings. The user can subsequently use the map to navigate previously traveled routes. Our system requires minimal training and no pre-existing building maps. Our system uses a combination of gesture and speech interfaces to make it usable for visually impaired users.

2. **Mobile Software for Typing on a Touch Screen Using Braille:** For visually impaired users, existing touch-screen keyboards are cumbersome and time-consuming. We present several prototype methods of text entry on a modern touch screen mobile phone that are based on the Braille alphabet and thus are convenient for visually impaired users. We evaluate the strengths and weaknesses of our Braille-based methods through a user study with 15 participants. Our results indicate that a spatially-oriented method of entering Braille using a single finger was preferred since it balances simplicity with accuracy. We discuss how insights revealed by our user study can help us further refine and improve the preferred method.

3. **Mobile Software for Reliable Cash Identification:** Despite the rapidly increasing use of credit cards and other electronic forms of payment, cash is still widely used for everyday transactions due to its convenience, perceived security and anonymity. However, the visually impaired might have a hard time telling each paper bill apart, since, for example, all dollar bills have the exact same size and, in general, currency bills around the world are not distinguishable by any tactile markings. We experiment with the use of a broadly available tool, the camera of a smart-phone, and several methods of classifying SIFT key-points to recognize partial and even distorted images of paper bills.

4. **Mobile Software for Clothes Matching:** This part of the work attempts to make a first step in computationally determining whether a pair of clothes, in this case of a tie and

a shirt, can be worn together or not, based on the current social norms of color-matching. Our aim is to give visually impaired persons the ability, using snapshots taken by their mobile phones, to independently and confidently be able to choose from their wardrobe which set of clothes they can wear together.

Chapter 2

Navigating Unfamiliar Indoor Environments: A Mobile Tool for Independent Way-Finding

Visually impaired people frequently have a harder time familiarizing themselves with new indoor environments. The predominantly visually organized society designs spaces in ways that create barriers to exploration for those without vision. Recalling already traveled routes requires sufficient information about the route to be communicated to and be readily remembered by the visually impaired person. This includes both having to remember accurate turn-by-turn information, as well as specific points of interest on each route, such as a particular office door, in order to be able to both use them as a point of reference and as a possible destination. However, this burden of having to build a conceptual map can be potentially alleviated by using a mobile phone to track the location and the movement of the visually impaired person within a building, giving navigation assistance upon request.

This work [66] presents the design and implementation of a mobile navigational guide that uses a combination of Wi-Fi and accelerometer sensor readings with a mobile device to learn and navigate unknown indoor environments. The navigational guide is designed to enable visually

impaired users to easily train the system and record new paths between two arbitrary points within an indoor environment in a single traversal and allows the user to navigate any recorded path in the future. During the training phase, the system correlates the physical trajectory of the user with the Wi-Fi and accelerometer sensor readings from the mobile device to construct a virtual topological map of each path. For navigation, the system infers the user's current location in the topological map and uses the Wi-Fi and accelerometer sensors to navigate the user to any pre-recorded end-point within the environment.

Designing a highly accurate and usable mobile navigational system for visually impaired users raises several fundamental challenges that this work addresses. First, while a mobile device has a wide range of sensors including Wi-Fi, accelerometer, camera, GPS and compass that could aid in navigation, not all of these sensors are suitable for visually impaired users for indoor navigational purposes. In practice, all these inputs are highly noisy and we outline the shortcomings of these sensors. Second, the accuracy of the navigational instructions provided to a visually impaired user in an indoor environment needs to be significantly high. These way-finding instructions, such as the announcement of turns, need to be accurate both in their content as well as in their timeliness. They should give ample warning so as to enable visually impaired users to react to their changing surroundings safely and promptly. Despite the large body of prior work on Wi-Fi localization [63, 86, 74, 28, 11], existing solutions have exclusively focused on localizational accuracy and not on navigation, a fact which makes them directly not applicable for the problem domain. Offering way-finding assistance to a visually impaired user in an unknown building might not be so much dependent on a perfectly accurate localizer, but on the ability of the system to compute the optimal route to the user's destination in real-time, continuously readjusting the up-coming instructions that would be issued. Third, navigating unfamiliar environments should require minimal training without any foreknowledge of the environment. In our usage scenario, we require users to be able to retrace a path with only a single training traversal of the path. Finally, the system has to be simple and usable by visually impaired users. The total reliance of a visually impaired person on his senses of hearing and touch, in order to move safely and successfully inside an unknown building, makes a careful design of the user interface of our system especially important. This is because the phone's default touch screen interfaces and visual interactions cannot be engaged or perceived by a visually impaired user, making the use of

an audio-based interface essential. In this work, we explore how to minimize audio interactions by using motion or haptic gestures which minimize the disturbances to the user's main cognitive task of sensing his surroundings. The overall contribution of this work is the implementation of a highly accurate, portable and easy to use indoor navigation system with very minimal training.

Based on a detailed evaluation across multiple different indoor environments as well as a user study involving nine visually impaired users, we show the following results. First, using a combination of Wi-Fi and accelerometer readings, our system is able to issue navigational instructions with an accuracy of less than six feet across a significant fraction of the paths; the worst case error was less than ten feet. Second, the navigation system could provide almost completely correct turn instructions within a few feet of the actual turn for almost all the navigation tests; in the worst case, for one of the paths, a turn was announced roughly $3-4$ feet after the actual turn was taken. All the participants of the user study were very enthusiastic in using and testing our system; all of the users expressed willingness in using such a system on their phones. 8 out of the 9 users expressed happiness in the level of navigational accuracy of the system when issuing turn directions, whilst the dissatisfaction of the single remaining user was based on the fact that he encountered technical difficulty when initially training the system. Most of the visually impaired users found our swipe gesture interface coupled with a transparent input overlay (to filter unnecessary user touches) to be very easy to use. In summary, we believe that this system, while not perfect, is a significant step forward towards realizing the vision of a usable and highly accurate mobile navigational indoor guide for visually impaired users.

The main algorithmic and UI contributions of this work are as follows:

- Provides a new Wi-Fi scan similarity measure which is more sensitive in distinguishing scans separated with differing physical distances than previous approaches.
- Offers a robust method of counting walking steps using a phone's accelerometer.
- Describes a method of creating a representative topological map of a building floor using similarities between Wi-Fi scans and distance information from an accelerometer.
- Details how to combine Wi-Fi sensing together with motion information from an accelerometer to improve navigational accuracy and the expressiveness of navigational instructions.

- Uses swipe gestures, which have a very low attention-grabbing effect, to indicate turns with a very high accuracy. To prevent users from accidentally invoking touch commands, we also provide a transparent input overlay to filter user's touch inputs to only allow our limited set of input gestures.

The technical workings of our navigational system can be summarized as follows:

From the set of sensors in the mobile phone, we use Wi-Fi scanning and the accelerometer to "sense" the environment for location and distance information respectively. Wi-Fi scans include the mac-address of each visible access point and its signal strength, as discussed further in section 2.3. This information can be used to construct fingerprints which are related to regions of space, but they cannot tell us how large of a region we are dealing with or whether a user is moving. So, in addition to Wi-Fi scans, we can use the accelerometer to determine lengths of such regions and how fast, if at all, the user is walking 2.3. While walking, the user can use swipe gestures to mark turns and use speech recognition to input labels of nearby landmarks, such as "Water fountain", as shown in section 2.5.

The Wi-Fi scans coupled with accelerometer and turn information enable us to construct a topological map of the floor automatically, as detailed in section 2.4.3. This map partitions space in a uniform and semantically logical way. Places on the map with quite distinct physical characteristics, such as those separated by turns, are delineated as such. Also, places marked as distinct in the same physical region by the system divide the space evenly. The user labels are then attached to these places, if previously recorded. The use of human labels is more memorable to a user than physical coordinates as explained in 2.5. Meanwhile, when issuing navigational instructions, information from the accelerometer is used to adapt the navigational algorithm, in order to predict the next location of the user. This improves navigational accuracy, in addition to the wording of the navigational instructions themselves, as demonstrated in section 2.4.4.

During navigation, the system uses text-to-speech as described in section 2.5 to prompt the user to walk straight or turn at the correct spots. The instructions are enhanced with distance estimations measured in steps, to help the user virtually sketch out the up-coming part of the route. Advance warnings are also provided both before turns and before arriving at the destination. Instructions can optionally be given as vibratory feedback if desired.

In short, Wi-Fi scans can tell us what locations exist and their topological relationship to one another. The accelerometer data can give us distances, without which navigational instructions would be less useful and without which navigational accuracy would suffer. The user can give names to locations which have a personal meaning and do not feel detached or static, section 2.5. These names of landmarks are given using the more natural input modality of speech, to prevent the delays and the inaccessibilities inherent in touch-typing. Turns are marked using fast and unobtrusive gestures across the phone's screen.

2.1 Problem Description and Motivation

The high rates of unemployment for visually impaired people, reaching up to about 80% in the United States [20], indicate that such persons are still, despite recent technological and legal breakthroughs, not realizing their full potentials. The inaccessibility of buildings has been for years a major hindrance to the free movement of such individuals, either due to unfriendly and even at times unsafe design practices, or due to the lack of Braille signage, such as door labels. The above coupled with the chronic lack of mobility instructors due to the fact that less and less people decide to follow this arduous profession, exacerbates the mobility difficulties of such individuals. The result is that many visually impaired people decide to stay in a familiar environment most of their time, such as their home, and do not actively seek employment or social opportunities outside it. This is because the lack of information on how to navigate an unknown building, would make a visually impaired person have to turn to a sighted guide for assistance, placing a social burden on both the visually impaired individual and the sighted guide. The following scenario elucidates the issue further.

Consider the case where a visually impaired person visits a new indoor environment (such as a hotel) with no prior knowledge. A small set of people within the environment initially volunteer to assist the visually impaired person within the environment to specific end-points of interest (such as a hotel room or dining room). However, the visually impaired person wants to be independent and not have to rely on others beyond a few initial interactions. Our goal is to provide a mobile navigational guide, which without any foreknowledge of the indoor environment and with little training, would be able to repeat any part of a route in the building. This system

should be able to "sense" its surroundings and collect relevant location and motion information, data which could be used later to determine accurately the location of the user inside the building and provide navigation instructions to a user-specified destination, like the ones that the user would have had to remember in the absence of such a system, including informing him on when a turn or when the destination is approaching.

Designing such a navigation system requires us to address several challenges. Given the target audience and the problem setting, the system should be *highly portable* and *easy to learn and use*. To work in unknown environments, the system cannot rely on complicated floor maps, which require a lengthy preparation procedure, [85], building structure models [35] or pre-existing geographic information systems [53]. The need for portability implies that no heavy equipment, such as a portable computer, [75], or a costly and hard to set-up server farm, [32], should be required or even assumed to be available. Existing commercial aids for the visually impaired are also not as suitable as might be deduced at first glance. This is because such aids might be expensive while being fragile, or, simply be quite awkward to carry around. Some examples are ultrasonic canes or laser glasses. At the same time, solutions based on sensitive or heavy equipment, such as camera glasses, a robotic guide dog [45] or a wearable computer, are also cumbersome. On the one hand, the above equipment places a burden on the user who now has to carefully look after such devices given their expense. On the other hand, such specialized devices may create a non-esthetic appearance for their visually impaired users, who might feel singled-out.

These constraints lead us to the use of one device, which is nowadays available in every pocket, the mobile phone. Not only is the mobile phone ubiquitous but it is familiar to the target group [39], lightweight and above all is equipped with an array of sensors which we can use to our advantage for effective tracking. Employing the above sensors, however, can be algorithmically difficult since the sensor readings can be highly erroneous. It has been shown in the literature numerous times, however, that the signal strength of neighboring Wi-Fi networks can be used to determine an approximate location of the user without necessarily knowing the topology of the Wi-Fi beacons, [28, 17, 60]. A significant question that remains is how can we avoid the need of ready-made floor maps or building models? The solution is to employ the user as the initial trainer of the system. Given that this operation should be carried out once, we feel that the

social burden is much lower than having to ask for assistance or reassurance more often. The costs of acquiring such ready-made maps or models in a lot of buildings are also prohibitively high and would require specialized skills.

Any electronic navigational aid, however accurate, cannot be the sole mobility guide to a visually impaired user. This is because many obstacles and other ground anomalies may not be capture by such a system, even though their detection is essential for a safe mobility. The sensors' accuracy and computing power required for such an endeavor would be prohibitive, whilst algorithms for such an accurate steering are yet to be perfected. The physical world's complexity creates a moving target for the designers of such systems who cannot certainly anticipate everything that can "go wrong" in a fast-changing environment. In addition, movable furniture and other humans who might be walking around the vicinity offer additional challenges to an electronic navigational guide. As a result, current-day commercial navigational systems are limited to offering turn-by-turn directions.

In fact, visually impaired users make extensive use of hearing and touch in order to explore their surroundings and identify suitable landmarks which could assist in determining their location. Landmarks that could be employed for finding a specific room, for example, could include the presence of a wall with a certain feel or even the absence of a high obstacle, such as an open door at a certain point along a corridor. Hence, any electronic navigational aid, however accurate, cannot be the sole mobility guide and should not over-ride conventional mobility aids, such as a cane, or overload the information received through the senses of touch and hearing.

2.2 Related Work

Location tracking and movement detection have been the focal-point of a set of bourgeoning applications. On the location tracking side, chief amongst them are applications providing mapping, driving directions and social networking services. Other scenarios including Crowd-sourcing (for vehicular traffic estimation or for gathering location data [70, 2]), for security (such as tracking of stolen or rogue devices [79], for better scheduling of everyday activities and regulating phone functions depending on location, such as [36], have been proposed in the literature. Regarding movement detection and measurement, the greatest areas were such techniques have been

employed are in medical care and fitness [93].

In general and according to the survey carried out in [50], localization systems in the literature can vary in the way they describe locations using physical coordinates, or, relative or topological using natural language; the last being the approach followed in this work. The localization algorithms themselves can be categorized into those which use the signal strength, the signal's angle or the time of arrival. The localization unit can either be a transmitter and thus be localized by various stationary receivers like in sensor networks, or, be a receiver sensing the signals of several stationary transmitters [50]. Earlier related work used one of sonar, vision and laser sensing technologies, in both mainstream systems, [86, 74, 59, 14], in addition to systems built specifically for the visually impaired community, [45]. However, the high cost, the difficulty of deployment and the high demand of computational resources is problematic for large-scale usage of such work.

An empirical method for finding the user's physical coordinates on a map grid using Wi-Fi signals was proposed in the Microsoft Research RADAR location system [63] and further extended in works such as [10, 46, 47, 48] and more recently in [11]. In [11] GPS was used to opportunistically capture physical coordinates at building boundaries which were in turn used to bootstrap a Wi-Fi signal propagation model which localized indoor Wi-Fi beacons and devices. However, in our own experiments GPS was not visible at all inside the building, even at boundaries, and one had to leave the building and wait for some time for the GPS receiver to return any useful data.

For their location tracking algorithms a number of techniques were proposed, such as probabilistic Bayesian Particle Filters [29], nearest neighbor-based, neural networks [3] and support vector machines [8]. An accelerometer in conjunction with the Wi-Fi signals is used in [55] to improve the accuracy and precision of the localizer in an online manner, as well as providing directionality information. The fact that a user is moving or not (a motion model) is also found to be important in [58] and to improve the accuracy of a Bayesian Wi-Fi localizer in [4]. In Simultaneous Localization and Mapping (SLAM) [80], a robot can simultaneously build a map of its environment while traversing it. This usually requires input from a number of different sensors with statistically independent errors.

However, the general drawback with the above systems is that they require either a dense

installation of the Wi-Fi sensors, such as in every office, or a lot of training. Our work proposes a system which is trained by the user and which does not require having any notion of physical coordinates, a fact which also eases the semantic labeling of locations. Traditionally, their goal was to minimize the localization error which was defined in the literature as the mean or median squared error in Euclidian distance, i.e. the distance between the predicted and the actual Cartesian coordinates. The reliability of such systems can then be determined using the variance of the error. However, one may wonder in what way such a description of the error is interpreted when a localization system is used to aid in navigating a person on a route. Moving correctly on a route involves making the right turns on time and at the right place, avoiding obstacles while verifying your location by observing landmarks. All of these requirements are not tested by the error function used in many traditional localizers and thus a more empirical approach is followed when evaluating our navigational algorithm.

Concerning the design of a touch-based user interface, [89] describes and evaluates a whole array of multi-touch gestures which can be used in rich interactive applications. Amongst them is the "flick" gesture, a long and fast swipe motion across the width of the phone's screen, which we also employ. Our system draws on the experience of [38] when attempting to make the phone's touch screen accessible. In that paper ten subjects who were blind were given access to the iPhone for the first time. This was achieved by employing different types of touch gestures depending on the task. According to [38], these gestures were easy to memorize but hard to confuse with one another or to accidentally invoke when related to sensitive operations. For example, moving through a list of items was performed using a flick gesture whilst the more "dangerous" gesture of activating an item required two fingers to perform. Further, in their comparative analysis between using an iPhone and a more traditional phone with buttons, [38] found that users expressed more satisfaction and increased enjoyment when using the former, even though they were faster when carrying out the tested tasks on the latter. This demonstrates that touch interfaces, given their novelty, might engage the blind users more than traditional button-based interfaces by arousing their curiosity.

2.3 Sensors

In this section we describe the various sensors available on a mobile phone, we detail the obstacles encountered when attempting to use these sensors for way-finding purposes and we explain our findings which led us to specifically focus on the Wi-Fi and accelerometer sensors.

2.3.1 Choosing the Right Sensors

Modern smart phones include a variety of sensors, amongst them a Wi-Fi card, an accelerometer, a compass, a GPS receiver, a camera and a microphone. A Wi-Fi card which, by periodically scanning for neighboring beacons, can "sense" their signal strength, provides as with an energy wise cheap albeit a noisy sensor, [42]. Similarly, an accelerometer can be a low-power solution to "sense" movements, however, its signal is also noisy and contains all the movements that a user's body might make, ranging from the minutest shaking of the arm to the abruptness of someone being pushed, most of which do not represent walking.

Since our system should work indoors the use of a GPS receiver was deemed to be infeasible. This determination was arrived at after testing which showed that GPS satellites were only visible outside the building boundaries and at times stable coordinates were returned only after a considerable amount of time had elapsed in order for the GPS receiver to acquire a fix. This result rules out the use in our system of the most accurate but power-hungry [42] location sensor. At the same time, a navigational algorithm which can detect user motion and location using Wi-Fi signals still cannot determine the directionality of the user without employing a compass or waiting for the user to move a certain distance before determining the direction in the map towards which he is walking. Moreover, the usefulness of a compass while constructing a topological map by the system is apparent as without it the orientation of the whole map would be absent. However, after attempting to smooth the noisy signal provided by the compasses on two of our phones, we found that it was not really possible given the sudden jumps and erroneous information that such a sensor would often provide. An explanation could be the iron structures and electronic installations in many buildings which provide a high source of interference for these sensors, coupled with perhaps a low quality of the compasses found in smart phones. Further

details concerning the experiments on the unsuitability of the GPS and compass can be found at the end of this section.

2.3.2 Using Wi-Fi Scans

For location estimation, we propose the use of Wi-Fi signals from wireless networks, which are already ubiquitous in most modern buildings in the Western world, such as apartment houses, hotels and campuses. The wireless 802.11 functionality is used to sniff nearby wireless beacons. These measurements of the strength of wireless signals should provide a sufficient fingerprint of the current location, i.e. given a new scan containing mac-addresses and measurements of their signal strengths at a point and a list of previously recorded scans, we should be able to find a rough estimate of the scan neighborhood in the collection of previous scans in which the new scan lies, with a sufficiently small margin of error. A scan neighborhood of a specific scan includes the scans which have been recorded close in physical space to that scan. To achieve this we assume that scans close together in physical space should exhibit similar characteristics, i.e. list a similar set of beacons with comparable signal strengths. Therefore, a similarity function must be defined which ranks pairs of scans which list a similar set of beacons with comparable signal strengths high, whilst scans which have few beacons in common and whose signal strengths are too far apart are ranked low. Further, any similarity measure should be able to discriminate scans which are closely located but which are clearly semantically separate via a physical morphology, such as a turn. The measure should be stable in places with weak beacon signals or diverse beacon densities.

The difficulty of such an endeavor lies in the fact that "Intrinsic noises in the signals caused by multi-path, signal fading, and interference make such task challenging", [42]. Beacons may "appear" and "disappear" intermittently, especially at the boundaries of buildings and in hallways with many physical obstacles. Even the human body can cause interference and thus Wi-Fi signals are expected to differ depending on the number of people currently walking around the building and how fast they are moving. Even in the simplest case, where a user is standing still or rotating slowly at a single location, we observed nearly a 20 dB difference between the maximum and minimum RSSI for a given access point. Given the fluctuations of Wi-Fi signals

Access Point	Min RSSI	Max RSSI
AP1	-78	-58
AP2	-91	-71
AP3	-79	-58
AP4	-96	-88
AP5	-92	-81

Table 2.1: Fluctuations of Wi-Fi signals while the user is stationary

at a point, designing a navigation system purely using Wi-Fi signals can lead to high localization errors. Table 2.1 illustrates the variations in signal strength extracted from a mobile device when standing still or rotating slowly around a fixed point. What is striking is that the difference between the minimum and the maximum can be as high as 20 dB which is a factor of 100 difference at the receive power levels.

To illustrate the poor localization accuracy obtained by using only Wi-Fi signals, we considered an indoor testbed with 23 Wi-Fi access points and ran four standard localization algorithms from the research literature: weighted k-Nearest Neighbors (kNN), linear ridge regression, kernel regression and neural networks. We trained these algorithms across multiple spots within the floor and tested it for random locations within the floor. We considered the basic versions of these algorithms and also optimized the parameters for our settings and found the minimum localization error was 10.2 feet while the unoptimized versions had a much higher error as illustrated in Table 2.2. Despite attempting to exhaustively fine-tune the various parameters of our neural network, the localization error was consistently over 16 feet. Similarly, kernel regression did not offer substantial differentiation over the other approaches. Finally, we unsuccessfully attempted to combine a neural network with our best performer, weighted k-Nearest Neighbor. Essentially, we used the neural network as a mechanism of producing extra artificial neighbors which were then fed to the weighted kNN algorithm.

A further complication which arises when developing software which probes the phone's Wi-Fi card for neighboring Wi-Fi beacons is that their signal strength, or RSSI, is represented in a vendor specific way. The RSSI is a value of one byte in length, denoting the signal strength for

Method	Average Error (feet)
Weighted kNN (unoptimized)	19.2
Ridge regression (unoptimized)	22
Weighted kNN (optimized)	10.2
Ridge regression (optimized)	14.4

Table 2.2: Localization error of standard algorithms

each visible Wi-Fi access point. However, the range, sign and scale of this value is not defined in a common standard and so some phone platforms represent RSSI in decibels whilst others in an even more arbitrary way.

2.3.3 Efforts to Smooth Compass Data

In our system, we originally attempted to employ the phone's compass to determine the user's orientation and thereby automatically mark the turns on a route. As a magnetic sensor, the compass can be very sensitive to fluctuations in the magnetic field caused by the proximity of metallic objects, electronic equipment and building infrastructure.

After the phones software has stored the compass readings, post-processing was carried out in order to remove noise. A moving window of readings is taken over the whole set of readings and the value at the mid-point of the window is replaced by the median of the whole window. After experimentation, we chose a window size of five. The window is then shifted one position forward and the process repeated. This helps to smooth the otherwise very jittery compass readings.

However, the meaning of the term median is not clearly defined over compass readings, which by definition are given in degrees. Thus, we have to define a circular median which can work over degree values. This is because there is no notion of greater than or less than in the realm of angles. This can clearly be seen by asking oneself, what is the median of 0, 5 and 355 degrees. The mathematically defined median = 5. But clearly the correct answer should be 0. After placing all our angle values on a circle, the circular median is thus defined by first finding the arc of the circle which is mostly covered by our angle values, i.e. by excluding from the circle the region which consists of the largest difference between all pairs of our angle values. This circular

median is then used in the above moving window filter, which we call, the circular median filter.

The second post-processing step acts to sharpen the difference in compass readings at the routes turns. This is for the sake of other algorithms which are used in other parts of our code-base, where we wish to be able to detect turns in the recorded route relatively fast. This is impossible if every time we wish to find all the turns in a routes graph, we were forced to use sophisticated turn detection logic which would try to locate all gradual changes in orientation and interpret them as turns of the right direction. Thus, our post-processing, using a moving window like the circular median filter above, finds all the turns and sharpens or moves further apart the orientations of the compass readings at each turn. One can say that this step removes compass noise caused by turning. This is achieved by finding the difference in degrees between consecutive compass readings and summing a moving window over these differences. One expects such a sum to be close to 0, if the differences in consecutive compass readings are due to noise. Otherwise, if the sum of differences is over a threshold, e.g. 60 degrees, a turn should be detected. The peaks amongst the resulting sums of the windows of differences, therefore, are the turns. So, the remaining compass readings in the window of readings where the peak has been detected are moved further apart by adding or subtracting a value proportional to the amount of the actual turn.

However, as is clearly visible in the following graph 2.1, the user's orientation returned by our compass has retained many of its Deviations from the expected orientation, even after being filtered through the above algorithm.

2.3.4 Attempting to Employ GPS

In [11], opportunistic GPS at the boundaries of a building has been successfully employed to provide the grounding physical coordinates to a mathematical model of Wi-Fi signal propagation, which could in turn compute the physical coordinates of the user. However, the Android phones that we tested regularly did not yield any GPS readings within our indoor settings as we observed the GPS signal only sparingly within building boundaries. Using other phones such as a Windows phone 7, while we were able to localize to within a building, different readings within the building yielded overlapping results; the northern portion of the building mapped to the southern portion

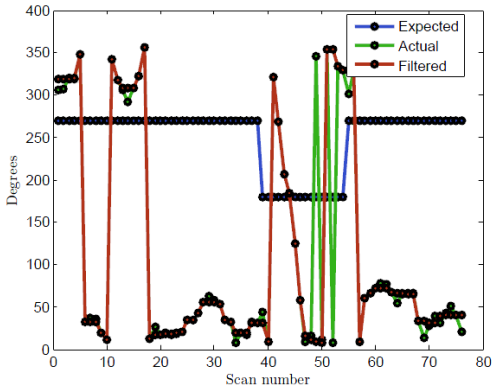


Figure 2.1: Expected, actual and filtered compass angles

and vice versa. Hence, we could not use GPS to even accurately distinguish between two corners of a building. GPS data captured from a laptop also yielded highly inaccurate results.

2.3.5 Reasons Against Using the Camera and the Microphone

In Surround Sense [1], many built-in sensors commonly found on mobile phones, such as the microphone, the camera and the accelerometer are used to measure the ambient sound, the lighting and color patterns and characteristic movements in a place in order to produce a fingerprint. It has been shown that this fingerprint can topologically identify a location, such as a shop or a cafeteria with an accuracy of 87%. However, in our case the use of the camera and the microphone were excluded because of mostly instability and privacy concerns.

A camera can only record what the user is pointing at. It would be infeasible to force the user to have to continuously point the camera at a source of more accurate location information, such as the patterns found on the floor, because a user would want to have free control of the position of his mobile phone and also because our subjects are visually impaired and thus it would be harder for them to continuously have to focus the camera at an exact target in a stable manner. On the other hand, taking opportunistic snapshots by the camera when the phone is pointed at the right direction automatically as in [1] is not guaranteed to capture the required information. Overall, it is questionable to what extent, for example, floor patterns can distinguish places which are

anyway located on the same floor as in our problem. In the same vein, microphone data cannot be stable enough to delineate between locations on the same floor to the same fine-grain extend as Wi-Fi, especially when taking into consideration that sound conditions in many places, e.g. classrooms, may change depending on the time-of-day and the current function performed in that vicinity, e.g. if a lesson is currently taking place. Finally, capturing camera and microphone data is a sensitive issue with privacy implications, which cannot be alleviated by simply algorithmic means, as even the possibility of such a violation might discourage potential users regardless of any algorithmically designed assurances to the contrary.

2.4 System Design

In this section, we describe how our navigational system builds a topological map of an indoor route using Wi-Fi and accelerometer measurements. We begin by detailing how to compare the Wi-Fi scans in a spatially meaningful manner and how to use the accelerometer sensor readings for counting the number of steps walked, before we outline our map construction algorithm.

2.4.1 Choosing a Wi-Fi Similarity Measure

Determining an approximation of the physical distance between two Wi-Fi scans is essential for building a navigational system. We tested a number of Wi-Fi similarity functions, two of which are shown in figure 2.2. Our functions represent the two Input Wi-Fi scans which are to be compared as two sparse vectors. Each vector maps every MAC-address visible at any one of the two scans to its corresponding Received Signal Strength Indicator (RSSI) value at the specific scan. Since most MAC-addresses are not visible at any given location, we assign to them an RSSI value of 0, a fact which accounts for the vectors' sparseness. Using the change in the visibility of Wi-Fi beacons and the change in RSSIs at each scan as the measure of differentiation, the similarity functions compute their costs as follows:

1. **Dice Coefficient:** Given two Wi-Fi scans,

   finds the number of measurements coming from the same source (having the same Mac-address) and divides two times this value by the total number of RSSIs from both scans.

$$\text{Tanimoto}(x, y) = \frac{x \cdot y}{||x||^2 + ||y||^2 - x \cdot y}$$

$$\text{RBF}_\sigma(x, y) = \exp\left(-\frac{||x - y||^2}{\sigma^2}\right)$$

Figure 2.2: Similarity function definitions

2. **Cosine Similarity Measure:** Given two Wi-Fi scans, finds the RSSIs which do not come from the same source, finds their dot-product and divides by their norms.

3. **Tanimoto Similarity Measure:** Finds the RSSIs which come from the same source, calculates their dot-product and divides by the norms of the two vectors squared minus the dot product.

4. **Radial Basis Similarity Measure (RBF):** Given two collections of Wi-Fi measurements, finds the RSSIDs which come from the same source and creates a normal distribution with mean equals the average of the squared element-wise differences between the RSSI values, times by their mean, and a width (variance) parameter determined experimentally to be 50.

The last two measures have proven the most capable in separating signal vectors from different locations apart as it can be seen in the following graph 2.3:

The graph 2.3 plots for both the RBF and the Tanimoto similarity measures, the average similarity between scans of 22 paths which are at the specified distance apart. We can see that, as the distance between the two scans is increased, the RBF similarity measure decays much more rapidly than the Tanimoto measure which does not react quickly enough to distance changes. This makes the RBF measure more reliable, even for scans which are only a small distance apart.

2.4.2 Counting the User's Steps Using the Accelerometer

In order to improve our navigational algorithm, it was necessary to furnish it with information on the user's movements. For example, the algorithm needs to be aware when the user is stationary and when the user is walking, and, be able to have at minimum some kind of notion of walking speed. Given that modern smart-phones come equipped with 3-axes accelerometers, it was

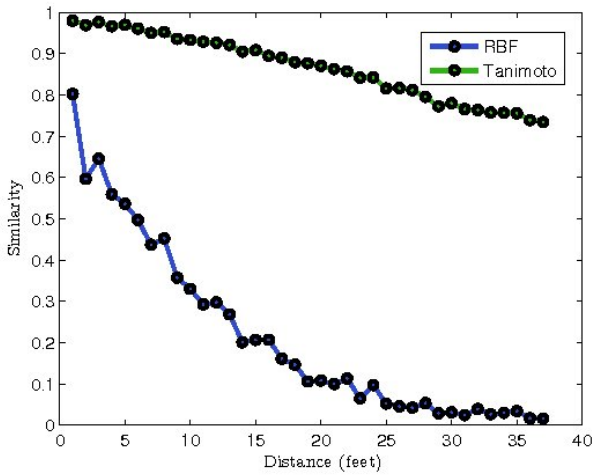


Figure 2.3: Spatial specificity of RBF and Tanimoto similarity measures

decided that a step-counter could be build employing these sensors which would fulfill the above needs.

Accelerometer readings, however, can fluctuate rapidly, regardless of the phone's model or manufacturer. A mobile user can potentially point the phone in any direction while on the move, making it difficult to compute the vertical axis of acceleration which could be used to count the number of steps that the user has walked. Simple actions such as rotating a phone can cause significant variations in the accelerometer readings across the three axes of measurements. In this section, we show how we can clean accelerometer measurements to provide a reasonable measure of the distance traversed by the user.

Our goals for the pedometer were that it should be relatively accurate, work on-line, do not consume excessive processor time or power slowing down the remaining of the navigational algorithm, do not require foot-mounted equipment or extra devices and not require a training phase. Accelerometer signals, especially those produced in a mobile phone, are usually noisy and sometimes unreliable. They are also not expected to provide data at a very high rate, more than perhaps 20 readings per second. Our algorithm, therefore, should operate with noisy input and be able to detect steps even with a small number of such inputs.

Unfortunately, algorithms found in previous work could not be used as is because they were

not designed with our specific goals in mine. The pedometer described in [93] requires a foot-mounted device to be present, for example, whereas the pedometer in our study should work in a mobile phone which might be placed at any position on the body. Since our pedometer needs to work on-line, the algorithm described in [49] where a fast Furrier Transform is used to discover the periodicity of steps in accelerometer signals could not be used due to the expensive processing requirements of FFT. Due to the different modes and styles of walking amongst various activities and individuals, a set threshold in accelerometer magnitude for detecting steps [57] could not be used, even if such a threshold has been found experimentally. Finally, the on-line nature of our algorithm precluded the use of any techniques with a training phase when determining any step detection thresholds, such as the one described in [31].

Instead, our pedometer algorithm works as follows:

1. An array of accelerometer measurements is continuously filled-up from the phone's accelerometer sensors. The size of the array is currently kept at 70. Once the array has been completely filled-up,, a snapshot is taken and it is examined to find and count the number of steps taken on a separate thread. At the same time, the original array is emptied and the process of filling-up the array is repeated in parallel.

2. The three axes of the accelerometer readings are smoothed independently by applying an exponential convolution by multiplying the whole of the readings array with a moving window of length five, containing coefficients giving exponentially lower weight to neighboring readings.

3. To find which of the three axes is the perpendicular one and thus the one containing step information, the variance of the three axes is computed independently and the axis having the largest variance is kept whilst the remaining data is discarded.

4. The derivative of the chosen axes is calculated and the readings of that axis are multiplied by this derivative to produce an array of magnified readings in order to smooth out noise.

5. The tenth and ninetieth percentiles of the magnified readings are computed, as it was discovered experimentally that peaks lie above and below these values respectively.

6. Both positive and negative peaks in the magnified readings are detected and counted. A peak is a reading which is above the high percentile value calculated above and below the low percentile value. Also, a peak has to be 0.65 times higher or lower than all its neighboring readings in the intervals down to and up to the previous and next peaks. In addition, peaks have to occur within at least a distance of ten readings from one another.

7. All sequential distances between each positive and between each negative peak are computed. The variance of these distances between the positive peaks is compared to the variance of the distances between the negative peaks. The peaks which have the smaller variance are the ones deemed to contain step information, since a lower variance of the distances signifies a more periodic signal. The number of those peaks is equivalent to the number of steps taken.

The above pedometer algorithm is designed so as to meet our previously stated goals of accuracy and efficiency. For example, the size of the array of recorded accelerometer readings is large enough to ensure a quite accurate step count, but it is small enough to enable on-line computation of the peaks without large delays between each pedometer update. The size is also kept at a value which should not affect performance when performing array operations on the readings array. The exponential convolution ensures that the signal is filtered so that outliers and noise are removed as far as possible. It is also a very simple and fast operation to perform. Meanwhile, rather than a more complicated approach using a computationally expensive method of principle component analysis, finding the axis with the largest variance is very fast and can thus be performed in real-time. This procedure provides an easy way to determine the axis of acceleration with the greatest movement and so isolate the axis in which step information is most likely to be present. In addition, multiplying with the derivative weakens the low-frequency components whilst magnifying the high-frequency components from the large slopes, most of which should represent actual steps. This removes more noise in the input signal. Similarly, by calculating and using percentiles as cut-off values for finding peaks, our algorithm does not rely on a pre-determined cut-off value and can thus adapt more easily to different walking styles by relying on the actual data to guide its decisions. As a result, a training phase is not needed. By ensuring that peaks are a specific distance apart, which in our case translates to around 0.5

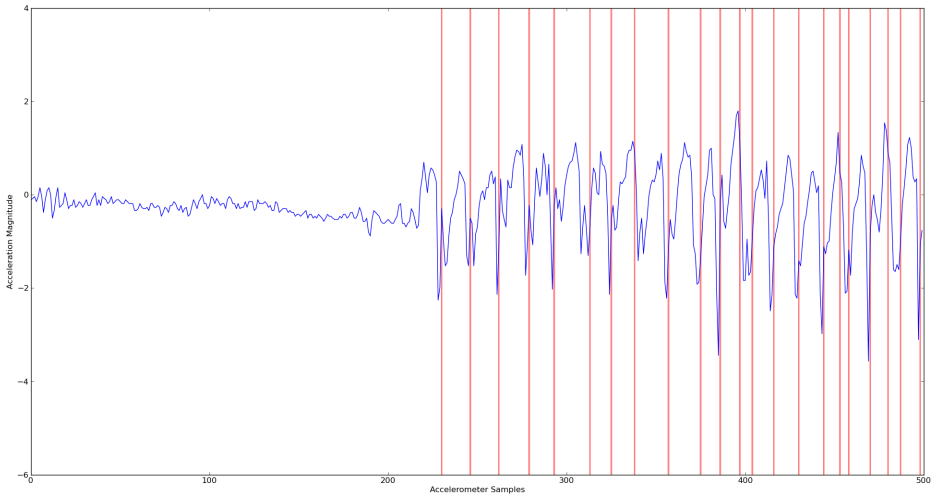


Figure 2.4: Steps counted on the accelerometer signal

seconds, the peak detection algorithm avoids over-counting steps thereby avoiding more of the problems of a very noisy signal. The fact that peaks have to be by a certain factor above or below all their neighbors also tackles more of the noise issue by eliminating local peaks. Rather than squaring or taking the absolute value of the readings, our approach of looking at the positive and negative peaks separately and choosing which one is authoritative regarding the number of steps taken, does not suffer from the fact that positive peaks mixed with negative peaks may actually over-count the number of steps as some of the peaks may be counted twice, both as positive and as negative peaks. In our observations, we have seen that usually peaks of one of the signs are informative, whilst the peaks of the opposite sign are usually too sparse and noisy. Choosing the right sign, therefore, removes such noisy input.

From the above graph 2.4 we can see that the pedometer algorithm ignores sudden or spurious jumps in the accelerometer signal but is quite accurate when counting the actual steps walked by a test subject.

2.4.3 Map Construction

According to [19], "humans do not appear to derive accurate cognitive maps from path integration to guide navigation but, instead, depend on landmarks when they are available". In other words, humans do not take into account Euclidian distance or angles when navigating but the previously encountered landmarks. Our map construction should therefore enable the user to easily mark places that he finds of interest, in addition to the route's turns. For them to be effective, such annotations should only cover a region of space large enough to accommodate a sufficient location context so that the user could identify it, but not too large so that it would encompass multiple semantically disparate places.

Our novelty is that Wi-Fi and accelerometer data from previously visited locations are laid out in a topological map and not, as traditionally done, in a Cartesian grid. This means that a single path is broken up into a number of segments called nodes, each one housing a collection of Wi-Fi scans representing a particular contiguous region of space. The approximate length of each node is also measured using the number of steps walked at that particular region of space as estimated by the accelerometer data. This approach, frees our localization module from the burden of requiring extensive floor maps, which are in any case difficult to come by. Training and labeling of the topological map can be carried out directly by the user, by simply taking note and thus labeling turns and landmarks while traversing a route for the first time. Employing a topological map makes its nodes more amenable to labeling as described above, but also provides us with an interesting experimental query: Can we achieve higher accuracy of navigation on a more course-grained representation of space than the traditional way of using a thickly covered grid?

While navigating an already recorded path, the user's approximate location could be determined by comparing the sensory data present on the previously constructed topological map with the current sensory input. In this approach, the grouping of scans into nodes can improve localizational accuracy. This is because given a single scan representing the user's current location, it is more accurate to identify the similarity, and thus the physical proximity, of this scan to a group of other scans representing a region of space, i.e. a node on a topological map, than to unrelated pairs of other single scans scattered around the space. Given the high level usage scenario of the

system, using a single scan for tracking and navigation is essential as Wi-Fi scan probes take around 0.7 or more seconds on all of our test phones. Waiting instead to get a window of scans, would slow down tracking considerably making way-finding less safe and effective.

Segmentation Algorithm

As summarized previously, in order to train the system, the user walks a path and along the way marks all turns and records labels for any landmarks, such as "Door to the Cafeteria". During this phase, the system scans for Wi-Fi networks logging their mac-addresses and signal strengths, every around 0.7 seconds which was the fastest rate achievable on our mobile devices. At the same time, it counts the number of steps being walked. After the path has been travelled, the segmentation algorithm splits the Wi-Fi scans into sequential collections of map nodes using the step count information as a parameter. Edges are created in the map between nodes labeled with turn indicators based on the turns that the user has marked along the path.

For the segmentation algorithm to be effective it should work fast and should not struggle to scale, as the number of Wi-Fi scans is dramatically increased. This is because a path can be from tens of scans in length to hundreds, and splitting them into map nodes should at most take a cubic time in the number of scans so that it does not discourage potential users of the algorithm. Our solution meets this challenge by using a dynamic programming approach which tries to minimize a cost function over all the set of possible sequential scan splits. More formally, given an existing sequential split of scans into nodes up to scan i, it attempts to find the next split which will minimize the node creation cost function of node $i+1$ to j, where j can be from $i + minNodeLength$ to $i + maxNodeLength$. This meets the cubic complexity requirement of our goals. Defining a cost function over a sequential split of scans can be done easily by observing that:

1. Scans within a node should have a high mutual similarity (intra-node similarity) but should exhibit a relatively low similarity with the scans of neighboring nodes (inter-node similarity). Finding sequential groupings of scans which improve intra-node similarity whilst decreasing inter-node similarity should, therefore, be preferred.

2. A node with turns amongst its scans should be less desirable than a node with no or less

turns inside it.

3. Nodes above a certain length (cut-off value) should be less preferred as their length increases. This is to penalize longer nodes, whilst the cut-off value exists to prevent very small nodes of getting a lower penalty. The pedometer measurements taken during training could be used as the measure of the length of each node.

4. Nodes containing scans with a higher variance in their similarities should be discouraged, whilst nodes containing scans with a smaller variance should be preferred.

To find the similarity amongst the scans of one node or between the collections of scans of neighboring nodes, the previously developed Radial Basis Similarity Measure can be used, by taking the average similarity of all pairs between the scans of the single node or of each pair of scans coming from each of the two neighboring nodes. The exponential function can be used to make the scale of the five above costs (intra-node, inter-node, turn, length and variance), be comparable. To further calibrate the algorithm we could also use a cut-off value below which the diminishing effects of the intra-node similarity on the magnitude of the cost are not considered. The sum of the above five costs can be weighed and thus empirically tested to find a cost function which with attain the right balance amongst them.

Our evaluation criterion is the fact that Wi-Fi readings taken while standing stationary should be grouped into a single node, whilst scans taken along a path should be split into nodes which cover the space in an evenly manner and which do not encompass turns inside them. In other words, we should show that maps are stable and only have a single node in them when the user is not moving. They should contain multiple relatively small but not minute nodes when representing a long path with separate nodes at each side of every turn.

Sensitivity analysis of the above cost weight parameters shows that the intra-node similarity and the turn cost are the most important in creating a map meeting the above evaluation conditions. In addition, it was determined that both the intra-node similarity and the turn cost should be weighed equally and thus were assigned the same weight of 1.0. Finally, the cut-off value of the intra-node similarity was empirically set to 0.7.

2.4.4 Navigation

Provided that the user has traversed the same path once in the past, our navigational system should determine a user's location, find the best path to a destination, and give meaningful instructions along that path. While attempting to navigate an already constructed map, the system must track its belief about the users current location on that map. We utilize the Bayesian filtering framework, well described by Fox et. al. [21], to integrate our estimate of the signal distribution at each location with a model of how much the signal distribution changes as a person walks for a particular number of steps.

Bayesian Filtering

Different sensors provide different inputs and different resolutions. They can never be completely exact and might be noisy. So, a mathematical technique has to be used to deal with the issues arising out of these complexities. In our case, this technique has to also be probabilistic, given the complex propagation characteristics of the Wi-Fi signals which cannot be modeled accurately. A Bayesian Filter can provide a statistical view of location tolerant to noise.

Formally, we observe a sequence of Wi-Fi scans $s(1), s(2), \ldots, s(t)$ and maintain a time-varying belief vector $Bel(x(t))$ which is the probability of the state $x(t)$ conditioned on all sensor data available at time t. $Bel(x(t) = i)$ designates our belief that the user is at map node i after we have received a signal vector $s(t)$. This Bayesian filtering framework includes two components: the perceptual model and the system dynamics.

1. The perceptual model encodes the probability of obtaining sensor input s given being at node location i. In our case it represents the signal distribution at each map node and describes the likelihood of making the observation s given that we "believe" that we are at $x(t)$. We implement this model by normalizing the distribution of similarities between all the nodes in the map and the current scan observation, similarities which are computed using the RBF similarity function, to create a distribution over nodes.

2. The transition probabilities, or system dynamics, encodes the change in the belief over time in the absence of sensor data. In our case, it captures the spatial connectivity of map nodes

and how the system's state changes as the user walks. Nodes which are closer in the map have higher probabilities of transitioning from one to the other and nodes which are far away have lower probabilities. These distances are embedded in the node information as captured by the pedometer while training.

Localization tracking happens iteratively as signal vectors are received and used to refine the systems belief vector. Transition probabilities should reflect or at least be comparable to the probabilities of reaching node j from node i within one step. However, when the user has not changed nodes, i.e. when still walking within the bounds of a single node, the probability of staying within that node should be smaller for shorter nodes and larger for longer nodes. In other words, the transition probability between two nodes should be inversely proportional to the distance between them, whilst the probability of transitioning between a node and itself should be proportional to the node's length. To calculate transition probabilities the following reasoning is followed:

1. We first observe that since paths are essentially a chain of nodes, there are two ways of leaving a certain node once the user has entered it:, i.e., by walking forward or by walking backwards to the two nodes adjacent to it. If the node is divided into s steps, then there are $2 * s$ choices of movements that a user can take within one step. Only two of these will lead the user out of the node.

2. The probability of staying at a node is defined as $nodeLength-1$ / nodeLen, where $nodeLength$ is the number of steps in that node.

3. The probability of leaving a node should then be defined as $1 - theprobabilityofstaying$.

4. Given a path of nodes $i_1, i_2, \ldots, i_n$, to reach node i_n from node i_1, one should leave nodes i_1 to $i_(n-1)$ and stay at node i_n. So, the probability of reaching node i_n from i_1 should be the product of the probabilities of leaving nodes i_1 to $i_{(n-1)}$, times the probability of staying at node i_n.

Calculating the next belief involves simply multiplying the transition probabilities with the previous belief in order to account for the effect of user movement. Then, and having received

Room No.	312	311	310	309	308	307	306	305	304	303	302	301	Destination
Node	1	2	1	3	5	4	6	7	9	10	14	13	16

Table 2.3: Node numbers adjacent to rooms in a long corridor

Room No.	312	311	310	309	308	307	306	305	304	303	302	301	Destination
Node	1	2	2	2	5	7	7	10	12	14	14	13	16

Table 2.4: Node numbers after using current nodes buffer in same corridor

a new Wi-Fi scan from the environment, this result is multiplied with the probabilities of the conceptual model, i.e. with the probabilities of being at each node given the new scan. This final result is the new belief.

The Stabilizing Effects of a Current Nodes' Buffer

A fundamental deciding factor when employing a Bayesian Filter is the requirement to handle noisy and unstable sensory inputs. However, in our experiments we have observed that despite this precaution, the estimate of the current node is at times unstable, jumping from one map node to another, even jumping among nodes that are not close together in space as is visible in the following table 2.3:

To prevent jitter in the estimate, we propose the use of a current nodes' buffer of size three. When a new location is determined it is added to the buffer, displacing the older entry. When the system is requested to find the user's current location, it does not simply return the current estimate, but the estimate having the majority in the current nodes' buffer. If no estimate is repeated more than once and thus there is no majority, the previous estimate is returned until a majority is attained. This has a smoothing effect on the returned estimates, whilst eliminating erroneous estimates due to noise. The following table shows the majority node in the current nodes' buffer along the same path shown above, indicating that most of the erroneous estimates were avoided 2.4:

Improving Wi-Fi Navigation Using Motion Estimation

While providing navigational instructions, it may be beneficial to combine the feedback from the surrounding Wi-Fi signals together with the current step count provided from the accelerometer, in order to create a more stable and accurate navigational algorithm. As discussed above the two components of a topological Bayesian Filter are the sensory input, in our case provided by the Wi-Fi signals, and the transition probabilities, in our case calculated by the relative lengths of each node. However, it cannot be assumed that these probabilities remain stable as the user walks, since movement towards a specific direction should make the departure from a certain node and the arrival at another one more certain than the probability of being at any other node.

To incorporate pedometer input in the transition probabilities, we simply raise the transition matrix to the power of the number of steps taken between our previous and the current estimate. This is because each transition probability is calculated in such a way to represent the likelihood of making the given transition if the user takes one step. To incorporate a notion of walking in the transition probabilities we do the following:

1. We determine the possible movements made by the user. We do this by keeping a history of the previous probabilities of being at each node and comparing them with the current ones. We do this for all pairs of nodes. If the probability of being at node i has decreased and the probability of being at node j has increased between the previous and the current probabilities, we could assume that the user might have moved from node i to j. Similarly, if the opposite has happened and the probability of being at node i has increased whilst the probability at node j has decreased, then we say that it is not likely that the user would have moved from node i to node j.

2. Given the above findings, we compute the geometric mean between the previous probability at node i and the current probability at node j. We do this in order to prevent noise drastically influencing our results.

3. We then multiply the current transition probability from node i to node j with the calculated geometric mean, if we had found in step one that it is likely that the user has moved

from node i to node j. Alternatively, if it is more likely that the user has not moved from node i to j, we multiply by $1 - thegeometricmean$ calculated in step two.

Generating Navigational Instructions by Using a Step Horizon

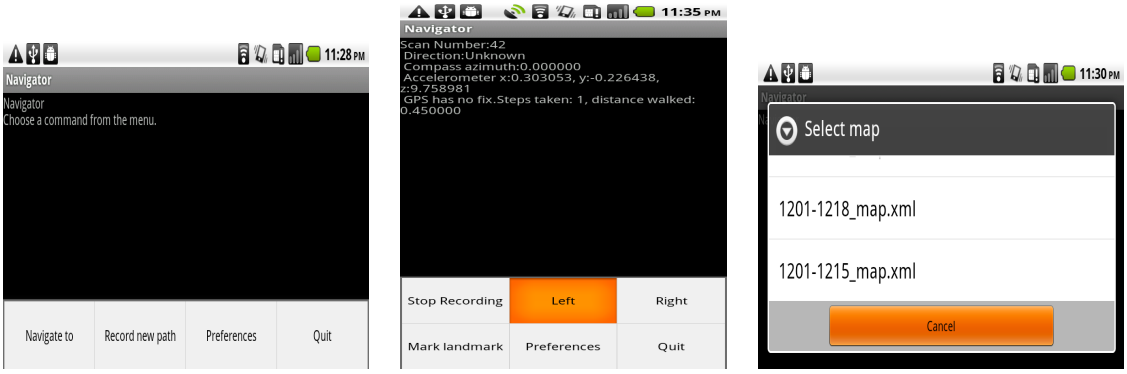
Taking the majority location from the Current Nodes' Buffer, the system calculates the shortest path to the destination. The system then gives the user appropriate instructions to walk toward map nodes further down the shortest path. Navigational instructions are derived using the length and directionality of map edges.

Certainly, instructing a user to turn after the actual turn, even if the instruction comes very close to the actual correct position is certainly a serious bug in the navigational algorithm. However, even if the instruction to turn or the acknowledgement that the user has arrived at his destination comes at the exact position where the turn or where the destination is to be found, this also does not make for a good user experience. A user needs to know beforehand that a turn is coming up so that he will plan ahead, especially when the user is visually impaired. This heads-up should come accompanied with an estimate of the number of steps required to reach the announced turn, landmark or destination.

In our system, this is achieved by means of a step horizon. The navigational algorithm, when deciding which instruction to issue, uses the current direction of motion of the user to predict along the path to the destination, if there is a turn or another important point of reference after a certain number of steps ahead, currently twelve. If a turn is detected on the path to the destination which falls within at most the above number of steps, it is pre-announced together with the number of steps required to reach it. The same for a reference point, such as the destination.

2.5 Usability and the User Interface

The interface of the navigational system provides the user with the option to either record a new route or to be guided toward a previously recorded destination. If the user wishes to construct a new route, they must merely walk toward some destination while the device passively samples wireless signal strengths and counts the user's steps along the way. Explicit user input is, however,



(a) (b) (c)

Figure 2.5: System interface: (a) Initial menu (b) Recording a path (c) Selecting a route

required at any turns along the path and for annotating landmarks.

Figure 2.5 shows the main menu of the application and the most important functions are "Record new path" and "Navigate to". When navigating the application's menu, the user uses a simple screen reader to read the menu and choose the appropriate option. We use a screen reader only in situations where the user is stationary. We do not use the screen reader when the user is in motion, such as while recording new paths or navigating to a destination.

In [38], most visually impaired users expressed their frustration and anxiety when using a touch-based phone since they could accidentally invoke a command unintentionally. In our system, we prevent this by placing a transparent input overlay covering the entire application surface, which filters the user's touch inputs allowing only scrolling and turn instruction gestures. Next, we discuss the user interface for recording new paths and navigating to a prerecorded destination.

2.5.1 Recording a New Path

Upon choosing to capture a new path, the application asks for the path's name which is the user-identifiable label for the path. While the user is walking along a new path, the mobile device records the relevant sensory information. A key feature of the UI presented when recording a new path is to allow the user to explicitly mark turns on the path.

2.5.2 Signifying Turns by Using Rotation

A navigational system must interact with the user in a modality suitable for that user's needs. One important restriction when designing an interface for the visually impaired is that the continuous use of a screen reader is undesirable due to the already important role of the sense of hearing in obstacle avoidance. Secondly, the availability of advanced sensors, such as accelerometers, only on the most expensive mobile phones together with the fact that almost all of these phones are touch input based, limits our choices of input methods.

As shown in Section 2.3, the compass was insufficient to accurately capture turns in a path. Originally, our interface used a novel idea of indicating turns which involved flipping the phone 90 degrees to the left or to the right. If the user wished to indicate a left turn, he would rotate the phone 90 degrees to the left and conversely if he wished to turn to the right. These motion gestures were used both when recording a new route and during navigating a recorded route. In this way the user did not have to interact at all with the phone's touch screen. However, during our experimentations and as demonstrated in section 2.3, we subsequently determined that Wi-Fi signals fluctuate substantially, even when simply turning the phone at a single location. Consequently, we decided to abandon this input mode of rotation gestures and develop a solution that makes good use of the phone's already available touch screen.

2.5.3 Indicating Turns by Using Swipes

In our subsequent iteration of the user interface we employ the phones touch screen as a mechanism for indicating turns. If the user wishes to turn left, they simply swipe left along the screen, after which the phone vibrates to signal its acknowledgement of the turn and optionally issues a text-to-speech output. For turning right, the user swipes right along the width of the screen and a similar but distinct vibration is issued together with optionally a speech output. These swipes have a quite natural character, are easy to perform and very hard to the phone to misinterpret since they are horizontal and cannot take the place of any swipes that could be misunderstood as indicating scrolling. To further prevent accidental swipes, the phone is programmed to accept only swipes which are above a certain threshold in length. The speed of a swipe could also be used to filter erroneous gestures, however, in our initial testing this was not found to be neces-

sary. During recording or navigating a route the phone's touch screen is also kept blank of any other interactive touch controls and only displays informative text for the benefit of the sighted assistant if required. Other interactions are carried out using the phone's standard application menu which can easily be accessed via a special button at the bottom of the screen.

The source location, the final destination, and any landmarks along the way are all optionally labeled using speech recognition. The speech recognition engine is provided by the phone's operating system and we use it here without any modifications.

2.5.4 Navigation

When using the system to navigate towards a known location, the user must select a desired destination from the systems database of recorded paths. It is acceptable here to temporarily make use of the screen reader, since the user will not be walking a route that he has not even started. The system then infers the users most likely location along the recorded path and issues walking commands such as Go straight for 20 steps, Turn left after 5 steps, etc.

Again, since it is preferable to not use the screen reader while walking we also have devised a small set of vibratory commands which are easy to learn. For example, one long vibration signals that the user should continue walking straight, whereas three short vibrations indicate that the user has arrived at their destination.

2.6 Evaluating Navigational Quality

In this section we evaluate the navigational accuracy of our system. First we determine how our topological-based Wi-Fi localizer compares to traditional Wi-Fi localization approaches. Then, we perform a case study with the help of a totally blind individual who was asked to walk a number of paths on different indoor locations while we were observing the accuracy of the system's instructions. This study with only a single blind individual was undertaken so that we could examine our system's practical performance, including carefully analyzing its accuracy and its usability, in the greatest depth possible. We also wished to do this before embarking on a larger study so that we could flesh out any technical issues still remaining. The next section takes this effort to its ultimate conclusion by performing a much larger user study with many

more visually impaired participants in order to gain multiple insides from a more diverse subject group.

2.6.1 Evaluating Localizational Accuracy on Straight Paths

Localizational accuracy is how much the user's physical location, as reported by the navigational system, deviates from his true location at that moment. Calculating localization accuracy is informative as it enables us to compare our system's performance to that of traditional Wi-Fi localization algorithms found in previous work. Since our navigational system does not use physical locations, accuracy has to be determined based on our map's topological nodes. On the one hand, determining the localizational accuracy of our navigational system depends on how well our map construction algorithm 2.4.3 breaks-up physical space into topological nodes which are representative of the building's physical characteristics. On the other hand, during navigation it depends on how accurately and quickly are incoming Wi-Fi scan probes are matched to the corresponding topological node to which they are physically closest. So, to calculate localizational accuracy, we can compare the user's current node as reported by the system while navigating a path, with the actual node that the user is currently in. To determine the actual node that a user is currently in, we can use pre-determined points in physical space which are situated within each node and use these points to find out where on our map the user should currently be.

In our case, a rough estimate of where in physical space each node starts and ends is discovered by laying out and marking on the floor a complete Cartesian grid. More specifically, we have divided the third floor of our main departmental building into a grid consisting of six units in the x-axis and ten units in the y-axis. Each x-axis unit is equal to nine feet and two inches and each y-axis unit is ten feet. We have devised this uneven arrangement of grid cells so as to be able to cover the whole floor in a practical manner, i.e. have grid lines correspond as much as possible with walls or centers of corridors.

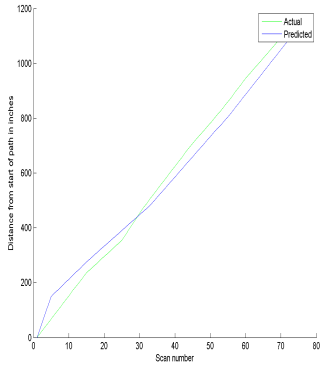
While recording a new path, we walk on our path normally until reaching the point on the floor at which we have covered exactly 1 axis unit, either in the x or in the y direction. Then, we note down the corresponding identifier of the Wi-Fi scan that is currently being recorded at that location. Afterwards, when the map with the topological nodes has been constructed, we

determine which Wi-Fi scans each node contains and therefore we can discover roughly around which region of physical space each node is situated. We can do this by interpolating from the locations of the scans we had just noted down in order to find out the approximate locations of all the scans on the recorded path.

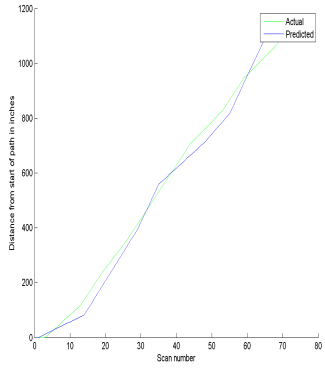
When the user navigates the path for a second time, we use sticky tape to mark on the floor where each node starts and where it ends and we then use a measuring tape to determine each node's actual length. In a similar manner as above, we record the node number the system is currently reporting when crossing any of our grid lines. By assuming that each node as a straight line of equidistant segments, each one corresponding to each of the node's scans, we can determine the approximate physical location of each Wi-Fi scan during navigating. In this way, we compute to what extend the estimated location of each scan during path recording matches with the estimated location of the same scan during navigating the same path.

Using the above methodology, we walked twelve paths on the third floor and recorded the locations of scans at each grid line while the phone was recording Wi-Fi and accelerometer data. We then walked the same paths disabling the pedometer and the transition model of our navigational algorithm so that it would not positively affect in any way the results of the Wi-Fi localizer. The localizational accuracy is determined by finding the mean Euclidian distance between the approximate physical locations of each scan estimated while recording each path and the location of the same scans estimated while navigating. The results are shown in the following graphs 2.6 where green lines represent the expected physical distance of each scan from the starting-point of its path, whilst blue lines represent the actual distance:

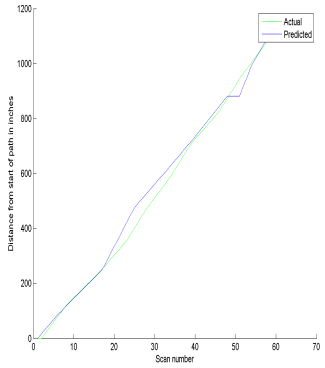
As can be seen from the above graph 2.6, our topological localizer achieved similar accuracy to previous work, i.e. around a mean of 3.6 feet. Even though we depict only straight paths, we nevertheless attempted to calculate the localizational accuracy of paths with more complicated shapes too. However, it is difficult to determine the approximate location in space where a node's scan is situated, when a topological node is not a straight line but can span a wider region of space. Inherently, our topological localizer works on a very different concept from traditional localizers, making direct comparisons beyond the straight line case non-trivial and even unfair.



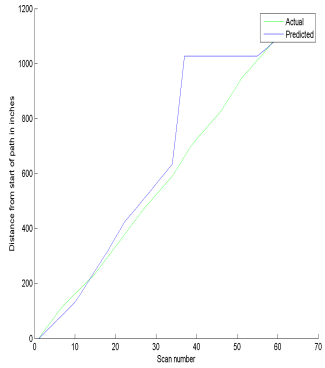
Path 1



Path 2



Path 3



Path 4

Figure 2.6: Expected vs. actual physical distance of each scan from start of path

2.6.2 Measuring Navigational Accuracy

Navigational accuracy encompasses the effectiveness of all aspects of the navigational algorithm when guiding a user on a path. Not only the navigational instructions "straight, left, right, etc" should be correct but they should come at the correct time, neither to early nor too late, and the same with the pre-announcement of turns and the arrival to the destination. Thus, it is not easy to come up with a uniform and objective measure of navigational accuracy given the subjectivity involved when defining when the "correct time" is.

The best way to handle the above problem is to observe the system in its actual intended usage, i.e. test the system by having a visually impaired individual try out the system by first recording some paths with the assistance of a visual guide and then figuring out if the same individual can navigate the recorded paths without going the wrong way or taking the wrong turn. In our case, we decided to adopt this approach but make it stricter by also recording when the announcement of a turn or the arrival to the destination did not come at the exact point upon which the turn or the destination were reached.

We used an Android Nexus 1 phone for our experiments and the user was a totally blind user who is 29 years old with prior experience using mobile devices and speech interfaces for the blind. We tested our system across multiple floors in two separate buildings: A and B. We report our results across 23 separate paths across four different floors in buildings A and B. The two floors in building A had an identical layout while the two floors in building B had a very different layout. We chose these 2 identical floors to be able to check whether our navigational system was consistent and reliable in its navigational instructions if the Wi-Fi signals were to change slightly. The lists of Wi-Fi networks across the two buildings are also significantly different. Within the same building, the Wi-Fi networks also showed very different RSSI characteristics across different floors. We specifically chose paths which the user did not have much familiarity. The chosen paths ranged in complexity from the simple straight path, to paths with some turns at the end, to paths with a U-shape or to those with multiple turns in both directions from one side of the building to the other resembling an H-shape. Each path was traversed exactly once and was retested at different times after the training phase (to eliminate time-biases).

Tables 2.5 and 2.6 show the accuracy of our navigation system measured across two metrics:

Correct	-2ft.	-3ft.	-4ft.	-5ft.	-6ft.	-7ft.	-8ft.	+2ft.	Total Paths
22	2	3	3	3	1	1	3	1	39

Table 2.5: Accuracy of turn instructions

turn instructions and destination announcements. Here, again, the main take-away message is that the accuracy of our navigation system is extremely high with median error rates less than $1-2$ feet in most cases. The user of the system also observed very few navigational inaccuracies across all the paths. From table 2.5, we see that from the 39 "Turn left/right" instructions, 22 of them or around 56% were issued to the user upon arriving at the exact physical location of the turn or upon waiting at that intersection for some seconds without taking the turn. A total of eleven turn instructions (around 28%) were issued a little bit early, ranging from two feet in advanced to five feet. This is a very short distance in length and also includes the distance of around one to two feet required for the user's body to enter the actual region of the intersection. In addition, five turn instructions (around 13%) were given at an even earlier location from the actual turn, as they were issued six to eight feet in advance of the intersection. However, given that many turns were pre-announced by our system before the actual "Turn left/right" instructions were given, the visually impaired user was expecting to find the turn in his route anyway. This makes the occasional turn instruction which mistakenly comes even six to eight feet in advance, not to be a problem in our experiments. Only one turn instruction was given after having to walk into the turn, but even in this case, the error was negligible ($2-3$ feet) that the user did not perceive it as an error. From table 2.6, we observe that on 18 out of the 23 paths or around 78% of them, the announcement of the destination took place at the correct location. Only around two announcements took place $2-4$ feet before the actual destination in advance. In addition, two announcements were given $8-10$ feet in advance of the actual destination's location. Finally, on one path, the destination was not announced at all but the system correctly indicated that the destination would be arrived at in "1 step". Together, these results demonstrate the high navigational accuracy of our system with very minimal training.

When interacting with our user interface, the blind user did not encounter any difficulties. The disabling of the phone's touch gestures, except of the menu activation taps and of the scrolling

Correct	-3ft.	-4ft.	-8ft.	-10ft.	+1ft.	Total Paths
18	1	1	1	1	1	23

Table 2.6: Accuracy of destination announcements

and turn flick gestures, successfully prevented any accidental user touches to be interpreted as a command to the application or to the Android OS. The flick gestures used to indicate turns taken by the user were also totally accurate, as they were interpreted correctly on all 23 of our paths and the user needed no training and experienced no delay when using them. Finally, the application's menus were easy to learn to use even with the admittedly simplistic built-in screen reader.

Despite the high noise of the Wi-Fi signals and the difficulty of localization accuracy as demonstrated in the high amount of training required in previous work, our system seems to be highly accurate for navigational purposes. This is because only on two paths the announcement of a turn or the arrival to the destination came after the fact, i.e. after taking the turn or bypassing the destination. These are the only times when our visually impaired user might have been lost in an unknown environment.

2.6.3 Observations

From the above results, the key algorithmic observation is that the weight placed on the transitional model of the Bayesian filter creates a trade-off between announcing instructions a bit early, or having to wait a bit before the instruction is announced. In other words, we can make the system too sensitive so that it will jump to nodes ahead faster or make it slower to adjust and create some delays. In this test run of the system, it appears that the right balance was achieved. However, in our second building there were no mistakes concerning having to wait for some seconds at a turn or the destination and there were almost no turns announced in advance. Whilst with the same system, in our first building, there were a few delays. So, an adjustment to the system's weight parameters might not be simple to perform as the parameters seem to be based on the characteristics of the buildings Wi-Fi.

Detecting that the user has arrived at a turn or the destination is exclusively based on reaching

the node at the specific turn or the final node of the route respectively. This somewhat inflexible approach can explain the fact that one of the arrivals to the destination was never announced, since the final node in the map for that route seems to have never been entered. A reason for this issue might be the relatively small length of the node in question, a fact which would make the Wi-Fi signature of that node in the map weak. Future experimentations should perhaps lead to an improved method of constructing maps in such a way to avoid any such problems.

2.7 Evaluating the System through a User Study

In this section, we summarize the design of our user study and give an overview of the demographic characteristics of our participants. Then, we list the users' impressions of our system and group them into pertinent categories based on which aspect of our navigational system they are related to. We give special emphasis to the system's strengths and weaknesses that the study participants have also chosen to concentrate on. Finally, we analyze the responses given by our study participants together with the observed system accuracy during the user study, to come up with a main list of improvements that should be undertaken as part of future work.

2.7.1 Study Design and Evaluation Methodology

We recruited nine visually impaired participants from the New York City area to take part in our user study to test our navigational system. Almost all of our participants were totally blind and only one out of the nine was partially sighted. This was a desirable user sample as totally blind individuals are the ones who would benefit the most from an indoor navigational system, whilst at the same time we did not want to exclude the feedback of the partially sighted from our study. There was variety in the sample concerning the time of onset of blindness, as a slight majority of the study participants were congenitally blind whilst the rest had lost their sight later in life. Our sample encompassed individuals of both younger and older ages, as well as both people who had used a navigational aid before and others who had never used one. Three of our participants were relatively young as their ages did not surpass the age of 30. Another three were in their fifties, whilst we had two participants who had an age of 60 and above. Our user sample included both novices as well as experts in the use of navigational systems, as five of the

Characteristic	Yes	No
Age $<$ 50?	4	5
Totally blind?	8	1
Blind since birth?	5	4
Uses touch screen phone?	5	4
Used a navigational aid before?	4	5

Table 2.7: Demographics of the user participants

participants had never before employed such a system, whilst four of them were already familiar with a GPS-based navigational system. In fact three out of the four had in the past tried or were currently using outdoor GPS-based software solutions that were specifically manufactured for the visually impaired. Since our system ran on a touch screen phone which requires a different mode of user interaction than a traditional keypad phone, we enquired whether our users had ever used such a device before. A slight minority of the people involved in our study had never used a touch screen phone before, whilst the rest were familiar with such a mode of user interaction. A summary of these characteristics of our participants are listed in the table below 2.7.

The software was tested on an Android-based phone. At the start of each session, each participant was given an overview of the navigational system, including an explanation of the software's operation. If required, users were allowed to familiarize themselves with the touch screen and to practice the particular swipes for marking turns. Each participant was asked to walk a number of paths in the same building in order to record them. The aim of this training phase was for the user to get a first feel of the route and for the turns to be marked in the system using the touch gestures. For this, the interviewer would guide the user on the paths to be recorded by either allowing the user to hold him by the arm, or by having the user follow him in a safe distance, depending on the user's preference. After the routes were recorded and the topological map constructed by the software, each participant was requested to walk each path alone, while being guided by the navigational system. The interviewer would stay beside the user of following him/her at a safe distance, while observing the performance of the navigational system. The user was expected to follow any directions that the system would provide to him/her

and the interviewer would only intervene if the user had veered sufficiently off course.

After all the paths had been walked, the impressions of each participant concerning the system were recorded using a questionnaire containing both quantitative and qualitative questions. A set of the quantitative questions tried to measure each user's satisfaction with the accuracy, the simplicity, the responsiveness and the safety of the system on a scale from 1 to 4, where 1 means "Strongly disagree" and 4 means "Strongly agree". Another set of similarly structured questions enquired if the users had found the system to be easy to learn, a useful mobility aid and if they were willing to use it on their own phone. On the other hand, the quantitative questions were open-ended and prompted the users to respond with a few sentences concerning the parts of the system they liked, disliked and list any additional features they wished to be added to it. At the end of each session, the person conducting the interview would enter detailed notes on what took place during each path walk, both during recording and when navigating. The interviewer would also write down any important detail or fact that was observed during the user's use of the system and which the participant had omitted to mention as part of the responses given to the open-ended questions.

The paths walked were almost the same for eight out of the nine users. These were four paths on the third floor of our main departmental building. This simple experimental design was preferred, as some participants felt more comfortable with the surroundings than others and as we did not wish to burden any group of participants unnecessarily. Some users for example, took longer to walk certain more complicated paths and most disliked having to switch floors. Furthermore, we did not want to use different experimental designs for different groups of users, due to the small size of our user sample.

All four paths included two turns each. Two of these paths were H-shaped and involved asking the user to walk from one corner of the building to the diametrically opposite one, starting from a classroom and arriving at an office at each respective corner. One path involved walking in a U-shape along the same side of the building. The last path required the system starting from one side of the building to direct the user to a specific office at the other side, three quarters of the way down a corridor. The last path was designed to test the ability of the system to direct a user to a specific door.

One of the participants was asked to walk the same four paths on the fourth floor of the same

building. This floor has an identical layout as the third floor. The experiment was undertaken in order to compare the behavior of the system on two separate floors having possibly different Wi-Fi topologies but an identical layout. Additionally, one other participant, after having walked the four same paths on the third floor, was asked to move to the thirteenth floor for walking another two paths, in order to test the system in a more open space. This is because the thirteenth floor houses the department's cafeteria, a trickier place to walk around, due to the place featuring a large sitting area. One of the paths tested the system by guiding the study participant from the elevator through the cafeteria to a classroom and by helping him find a particular chair. This chair was not easy to find, as it was situated two rows before the back of the classroom and towards the middle of that row of seats. Another path involved getting to the same classroom chair through another route which avoided the cafeteria.

2.7.2 Study Results

This section summarizes the results of our user study. On the whole, they demonstrate a navigational system which features sufficient accuracy to be used on short routes with limited complexity but which may behave inconsistently at times due to Wi-Fi fluctuations.

Walked Routes and Navigational Accuracy

For most users, the system gave correct instructions at the right locations. For the turns, sufficient advanced warning was given and the instruction to turn was usually issued very close to the exact location where the turn was located. The direction of the turn was usually reported correctly, unless the user had swiped the wrong way when marking the turn during the training phase, 2.7.2. However, out of the four paths that most users had walked, there was usually at least one turn or one arrival to the destination which was announced $5 - 6$ steps off, or in a few isolated cases as much as ten feet in advance. For example, once the system instructed one of the participants to "Walk straight for 19 steps" and then turn right, whilst the turn was actually after 21 steps. Another time the system told the same participant to walk seven steps and reach the destination, whilst the destination was after five steps instead. For two of the participants, the second turn on the one of the H-shaped paths was not announced unless the user had turn

a little towards the corridor at the start of which the turn was located. In the most egregious of cases, the arrival to the destination on the U-shaped path was announced 17 to 20 feet before the actual destination but the user was able to realize and correct the inaccuracy easily. When trying to locate a specific office door, the system usually directed our participants to another office which is right next to the office in question. However, these two office doors are right next to one another with only a wall's width in separation. Most users could realize this error using their sense of touch. The reliability of the system suffered somewhat when we tried to make it locate a particular chair at the back of a classroom on the thirteenth floor. Although a chair close to the target one, i.e. one row in front and two chairs to the left was repeatedly identified instead, the directions taking you to that particular chair were at times confused. For example, while the user was in the classroom the system would decide along the way to the chair that the user had arrived at their destination, to immediately change its mind to tell the user to turn the correct way towards the row where the chair was located. On the other hand, the path through the cafeteria did not pose any difficulties to the system. Overall, however, this handful of inaccuracies concerned only a small part of the traversed routes. As can be deduced by the ratings the participants gave our system, its general accuracy was sufficient for the tested routes, a fact also reflected in the users' comments and enthusiasm.

Questionnaire Responses

As depicted in the table 2.8, the individuals taking part in our user study rated our navigational system on a scale of one to four, by responding to a set of short questions, such as: "Is the system simple to operate?" For each question the table shows the number of users who chose each rating $1-4$, i.e. from "Strongly disagree" to "Strongly agree". These questions could be grouped into three categories. The first category, made up of the first two questions, attempts to measure the accuracy of the navigational system when announcing turns and arrivals to the destination. As can be seen in 2.8, the participants were overall relatively satisfied with the accuracy of the navigational system, as for both questions there was only one user who rated the system with a rating of two. However, whilst for the accuracy of the turns the users appeared to be divided between "Agree" and "Strongly agree", for the announcement of the destinations two thirds of the participants showed a strong approval.

Is the system...	Strongly disagree	Disagree	Agree	Strongly agree	mean ± std
Accurate when announcing turns?	0	1	4	4	3.33 ± 0.71
Accurate when announcing the destination?	0	1	2	6	3.56 ± 0.73
Simple to operate?	0	0	3	6	3.67 ± 0.5
Fast and responsive?	0	1	2	6	3.56 ± 0.73
Easy to learn?	0	0	3	6	3.67 ± 0.5
Safe to walk alone using it?	0	1	2	6	3.56 ± 0.73
A useful navigational aid?	0	0	3	6	3.67 ± 0.5
Something you would use on your phone?	0	0	2	7	3.78 ± 0.44

Table 2.8: User ratings of the navigational system

The second category included the next three questions which aim to evaluate the user interface aspects of the navigational system. It can be observed that the great majority of the participants were in strong agreement that the system was simple to operate and easy to learn, whilst the responsiveness of the system received a slightly lower rating by only one participant. The final category of three questions targeted the general picture that the participants had obtained from the use of the system. From these questions, the first asked the users to express the level of safety they felt when they were walking by following the system's guidance. From the responses, it can be seen that most users felt safe when relying on the system's guidance, as eight out of the nine participants chose a rating of three and above. The participants also found the system to be a very useful navigational aid that would help them navigate more independently in indoor environments, a fact that was partly supported by the very positive responses accompanying the next question. The participants' enthusiasm about the system was further demonstrated with the final question which asked the users if they were willing to use the navigational system on their own phone in the future, a question to which an even larger majority strongly ascended.

Discussion and Future Work

During this user study a set of nine participants were asked to walk mostly the same four paths on the third floor of our building. This was to compare if the results were the same among different users. We found that Wi-Fi interference makes repetitions of the same experiment give somewhat different results. This difference is very small and it concerns the exact points on each route where the directions are being issued. However, finding a particular door or a specific seat in a classroom when it is your specific destination might be important in some navigation scenarios. Even though our system would direct users to the correct destination by approximately a meter of accuracy, this might not be enough if a neighboring door or seat is near enough as to make the user accidentally knock on the wrong door or seat in somebody else's chair. For example, on the thirteenth floor of our building, the reliability of the system went somewhat down when we tried to make it locate a particular chair at the back of a classroom.

Nevertheless, our users generally praised the idea of implementing such a type of navigational aid, a system which they could see as necessary and useful in their own lives. They were enthusiastic about the whole project, a fact discernible from some of the responses provided to the open-ended questions of our questionnaire. For example, three of our participants when asked what they enjoyed most about the navigational system expressed their sentiments as follows: "I think it is a great thing." "I think it is an excellent idea." "I liked everything, I think it was great." Others when so far as to suggest that our system could be a viable addition to the existing GPS products which work only outdoors: "I love it. You have to commercialize it. So many people will benefit from it." "It is more accurate than the other GPS systems I am using for outdoors." Some users even described previous bad experiences they themselves had when walking around unfamiliar buildings. One particular user said that he enjoyed going on cruises relatively often, but the lack of a secure method of finding his way independently around the ship made it difficult for him to have the best experience. A navigational system like ours, the user suggested, would fulfill this need of independent mobility. This idea of the participant could work, provided of course that Wi-Fi networks would be visible on board.

Concerning the users impressions from the actual usage of the system, Participants found it capable and functional. They described it as relatively accurate when giving directions: "It

was mostly accurate on the position of the turns and the arrivals to the destination." "It just needs some minor tweaks. It terms of accuracy now it is off by around a meter." Some users requested that our system does not limit itself to indoor places. They suggested that we should start exploring the possibility of making our system work both indoors and outdoors. We believe that this desire stems from the fact that visually impaired users would prefer to have an all-in-one solution that could attend to their way-finding needs both when inside and outside buildings. "It is good indoors but it should be good outdoors as well." One user suggested that we use existing building maps where they are provided by the building owner or a third party mapping service, such as the electronic maps available for some shopping centers and airports. "And these are the places where such a navigational system would be useful, like I want to find my way to an airport gate or to a train platform." Similarly, two individuals proposed that the system should be enhanced so that it could warn them of any obstacles that might be on their path or of any abnormalities found on the ground in front of them. The former was interested in knowing if there were any permanent large objects blocking his way on the path, whilst the latter was more anxious to be informed whether the ground had changed or was safe to walk on: "Sometimes in the middle of the lobby they may have something like a sculpture or a fountain. How would the system navigate you around obstacles like those?" "Could it pick out different things on the floor like the floor is wet or slippery or 'There is a carpet in front of you in five steps'. Could it tell you if there is debris on the floor?" Perhaps we could accomplish this extra functionality by employing the phone's camera, making use of another widely available sensor, but further research would certainly be required in order to meet this goal.

The fact that the system was keeping its users continuously up to date on their progress through the path by announcing node numbers was considered helpful: "I liked the fact that it made you aware when it was working, through continuous speech feedback." Some users expressed dislike though, during the few times when the system was giving them directions that were quickly changing in a short distance. This rapid change of mind concerning the current user's position could take place when the sensory input was such that as to make the system oscillate between a set of different map nodes quickly. Since our system employs a probabilistic model to calculate the current location in order to provide appropriate directions to the user, it could conceivably be programmed to also calculate a confidence measure for the current location estimate. Then,

when trying to calculate the user's current location, the current estimate could be chosen to be the current location only if the confidence measure is above a certain threshold. However, during our experimentations, it was not possible to come up with a reliable threshold which would filter out uncertain location estimates but which would not fail to update the user's location when he/she has actually moved. As a participant of our user study has suggested though, we could instead surface this confidence measure together with each instruction we issue to the user. An additional piece of user interface could be provided through which the user be given an indication on how accurate the current instruction is. Alternatively, an instruction could be modified in such a way to reflect this uncertainty, e.g. "Walk straight for nine to twelve steps".

In the same vein, the presence of landmark information in the topological map could help make our navigational instructions to the user richer. As proposed by one of our participants, the system could use the provided landmark information to enhance the directions it provides by appending the user-provided landmark names directly to the end of specific instructions. For example, "Walk straight until you reach the conference room door", or, "Turn right at the Water Fountain". Where, "Conference room Door" and "Water Fountain" are names of bookmarked landmarks. So, instead of providing only steps counts and turn directions, we should provide enhanced instructions like the above.

Some users strongly wished to increase the frequency of updating the step instructions: "The time lag between walking a number of steps and the system actually letting you know the updated number of steps to a turn or to the destination." "It was lagging a bit behind. It couldn't keep up pace with my walking." A participant suggested that we could probably achieve this by shortening the length of each of the map's nodes, i.e. changing the topological map to be more fine-grained: "Perhaps divide the path into shorter sections so that (A) it will update the step announcements much sooner and (B) if it misses a section, the mistake wouldn't be that large." However, shortening the length of each topological node would be a double-edged sword, as it might make accuracy suffer instead. The fewer number of Wi-Fi scans that would be available per topological node could make matching them with live Wi-Fi sensory data to be harder. A proper way of achieving this is to use the pedometer during navigation in order to get an indication of the distance that the user has already travelled within a certain node. This estimate should then be subtracted from the number of steps that the user is asked to walk. Additionally, one of the

participants was obsessed with the accuracy of the step count reported in each of the instructions. Once, the system instructed him to "Walk straight for 19 steps" and then turn right, whilst the turn was actually after 21 steps. Another time the system told him to walk seven steps and reach the destination, whilst the destination was after five steps instead. He was annoyed about that and he said that if the system is not extremely accurate when reporting the number of steps that are to be walked, he could not consider it a safe system because he may walk into danger. The reason is that the algorithm of counting steps is too coarse-grained to allow itself to be calibrated for users with different walking strides, such as for people with different heights: "The steps were not very accurate because suppose I am taller than you I would be making less steps than you. How do you calibrate that?" Others found the step counter not as accurate as they would have wished: "I wasn't feeling secure because of the limitations in recognizing the step count. It was good but off." In the future, perhaps announcing distances in meters or in feet would remove the one size fits all approach of the current step counter: "If you give distances in feet or meters it will remove the variability of the step measure."

Currently, there is no way in our system for the user to correct an error in a path while it is being recorded, by deleting say sections from it and re-recording them. Additionally, there is no user interface enabling users to add landmarks or change turn directions after a path has been entered into the system. A participant proposed that we implement an on-line way of correcting mistakes while recording a new path: "You want to be able to delete on the go, while being guided the first time. Like create a system where you can pause, delete previous path sections, continue, etc." A related improvement should also be considered, whereby users are able to virtually browse and explore all the recorded paths without moving away from the comforts of their armchairs, making corrections if necessary. Such a feature would not only permit the correction of mistakes but would also help the users to familiarize themselves with the recorded routes better, allowing them to memorize these routes more easily.

A weakness that the users wanted to be remedied was the fact that the system as designed does not work across multiple floors. This means that if a route is started on one floor, it cannot finish on another floor. This is because we have not tested this scenario to ensure that Wi-Fi signals could be a sufficient method of determining the floor on which a user is currently being located: "How will it know on which floor you are ... say if you are on thirteenth or on the

twelfth ... I mean there is only a short ceiling between the floors ... how will it know?" In the future, more instructions need to be programmed into the system and the topological map may need to be augmented in order to handle stairs and elevators. Our pedometer algorithm may require modifications, as one of our participants shrewdly observed: "If I am taking an escalator or the stairs, it wouldn't calculate the right number of steps. If you are taking stairs and you are on an escalator there is no body movement and even if you are taking ordinary stairs, there is very little horizontal distance change but a lot of change in the vertical distance. How would the system accommodate that?"

Another important disadvantage of our system that was brought to the foreground by some users was the fact that the system is not able to provide corrective action and assist users who have veered off the recorded route to get back onto that route: "What if you get off your path. How would the system find which way you are now facing? And how would the system help you come back on the right path?" However, without access to the whole of the building's floor map or without a way to join already walked paths in order to try and construct such a floor map, it would be difficult to provide any corrective action similar to the one describe by the following participant: "If it overshoots your destination or a turn by some distance, would it say that you have to go back two steps for example?" Nevertheless, one of the participants commended the fact that the system could start or continue navigating from any arbitrary location of the recorded path and adapt its instructions accordingly: "I also like that it recalculated the road depending on your current location."

A possible way to help the user get back on the right path was put forward by a participant who explained that the system could try and calculate the distance that the user is away from the prescribed path and provide the user with this information. Since the system does not use a compass, the participant mentioned, it cannot give directions to re-orient the user on the right path, but it could at least give the user some estimate of how far he/she is from the path. The systems inability to put a user back on the correct path is due to the fact that the system does not have the new location the user has mistakenly walked to in its database and so it would match the new location to some totally irrelevant place on the recorded path. In this case, i.e. when the probability of being at any one node is too low, the system should switch to another mode where it would just calculate the distance that the user is from the right path and just

give him/her this information, since it cannot provide any other form of directions. This solution was thought by the participant to be a sufficient alternative given our constraints. Implementing this idea though will require us to find a way to calculate approximate distances between a set of known Wi-Fi measurements belonging to a particular path and some unseen Wi-Fi measurements outside the path.

Guiding a user around an unfamiliar building accurately necessitates the use of precise language when formulating instructions. This is even more essential in buildings which feature corridors with complicated junctions, corners which do not make right angles or large hallways. However, our system can only issue turn instructions which ask the user to make a full 90 degree turn. As it was observed by one of our study participants, our set of instructions needs to be enriched in order for the system to be more useful in the above situations: "... we need to figure out a system where the turns are not all 90 degree angles. ... Perhaps 'Turn slightly to the right', etc.?" Similarly, walking a route in reverse from the direction it had been recorded seems to require more testing as observed by one of our participants. The biggest issues were that the system could not figure out the orientation of the user correctly every time and that the first node of the path, i.e. the destination since we were walking the path in reverse, was not identified, perhaps due to the fact that it was too small. Therefore, appropriate measures must be taken to ensure that all nodes that could serve as the destination are sufficiently large in order to allow matching by the navigational algorithm. We should also try to find a way to tell the direction a user is facing from their motion, since we cannot rely on the phone's compass.

Concerning our user interface, participants' comments were directed at both capabilities of our system to provide navigational instructions using synthetic speech as well as using vibratory feedback. Currently the system repeats instructions using text-to-speech more than once if the user does not move to another node after five seconds. It was suggested that if the current instruction was a repetition of an instruction which had already been given to the user, we should add the word "repeat" to it. Meanwhile, after discussing the matter with some of our participants, it became clear that a number of them wished us to make the system work with voice commands in addition to the current functionality of marking landmarks with speech recognition. In fact, speech recognition functionality might not be necessary after all when recording landmark names, as recording the actual speech utterance directly in an audio file might be sufficient. This

is because the names of the landmarks are not searched textually in any way but they are presented as a list from which the user is asked to select a destination. This list can simply be made up of a selection of the original pieces of audio recorded using the user's voice for each landmark. In this way, no Internet connection would be needed as is the case now for the speech recognition service to work.

"Initially I did not know which vibrations corresponded to which turn or to which instruction." This revelation by a particular study participant made us realize that perhaps our vibration patterns were not distinctive enough to be easily remembered. Even though we have tried varying both the number and the length of each vibration among different instructions, we only varied the number of the vibrations between the "Turn left" and "Turn right" instructions. Also, after talking to a number of our participants, we discovered that they did not always notice the vibrations, when both speech and vibratory feedback were turned on. In the future, we should improve the vibratory feedback given after each user action to be distinctive for each command and turn vibratory feedback on by default for all directions given to the user, as in the current implementation vibratory feedback had to be enabled by each user.

While our user study was under way, we determined that our user interface should be modified in order to make the swiping gesture more resilient so that wrong turn directions will not be recorded. This need arose in the case of one of our user study participants where, the system was mostly accurate in its navigation instructions except that 3 out of the 8 turns were announced the opposite direction. This is the first time we had experienced this issue which makes it very plausible that during training the user just did not swipe the correct way causing these errors. In the future, the system should also be altered to give speech feedback when swiping to mark a turn in addition to vibratory feedback, as one of the participants had complained about the lack of such feedback: "Make it tell you which way you have swiped when indicating a turn so that you are sure that you have not swiped the wrong way."

Finally, more haptic gestures could be added to the system in such a way to make the use of the phone's screen reader even more redundant, or for enabling additional usage scenarios. For example, we envisioned above the virtual exploration of recorded routes by the user before actually walking them. This scenario might be useful for learning and experimentation purposes.

In summary, even though described as simplistic, the users praised the algorithmically more

complex facets of our system. These facets include the system's ability to discover their approximate location within a route they had previously walked and its ability to count the number of steps they had taken. In any case, an algorithmically strong navigational system which also presents a simple to operate user interface, was the design approach we had aimed for. One user specifically stressed that the fact that the system is "programmed" by the actual end-user and does not rely on pre-constructed maps is a positive aspect. The user was perhaps alluding to the freedom that our approach provides, namely the ability to employ the system in any building with visible Wi-Fi hotspots without previously involving the building's owner in the mapping process. In general, however, for the users' enthusiasm to last, we have to prove to them that the system could be accurate in many more settings and situations than currently tested. Our users need to get more time familiarizing themselves with the system and for us to let them train it and use it for some hours on various paths, in order to be able to provide us with more holistic opinions.

In future work, an automatic calibration of the system's weight parameters according to the characteristics of the buildings Wi-Fi might improve accuracy even more. Also, detecting that the user has arrived at a turn or the destination is exclusively based on reaching the node at the specific turn or the final node of the route respectively. This somewhat inflexible approach can explain the fact that in our original case study one of the arrivals to the destination was never announced, since the final node in the map for that route seems to have never been entered. A reason for this issue might be the relatively small length of the node in question. Future experiments should perhaps lead to an improved method of constructing maps in such a way to avoid any such problems.

2.8 Summary

This work has presented a practical and useful navigational aid, which can remind visually impaired people how to independently find their way on any route they had previously traversed once when using sighted assistance. Its minimalistic gesture-base interface has made it simple to operate even while holding a cane or trying to listen to environmental sounds. Despite the high noise of the Wi-Fi signals and the high amount of training required in previous work, our

system seems to be very accurate for navigational purposes. From the 23 paths tested in our original case study, only in one path the announcement of a turn came after taking the turn itself, making it the only time our totally blind user might have been lost in an unknown environment. Similarly, based on our detailed user study with nine visually impaired users, we found that eight out of the nine users found our system very easy to use and could successfully navigate different paths in an indoor environment. Overall, we believe that this system, while not perfect, provides a significant step forward towards realizing the vision of a mobile navigational indoor guide for visually impaired users.

Chapter 3

Typing on a Touchscreen Using Braille: A Mobile Tool for Fast Communication

The fast and widespread adoption of mobile phones which use only a touch screen for input has created several accessibility challenges for visually impaired individuals. These challenges include navigating a primarily visual user interface, finding numeric buttons to enter phone numbers and typing text on a purely visual keyboard.

Improving interface navigability for visually impaired users has been dealt with in [39] through a set of gestures which allow the user to move around the UI controls and listen to their contents. Commercial implementations of this interface now exist [33]. However, concerning text entry, blind users are still forced to use the built-in on-screen keyboard. Even though this keyboard may be able to speak the character above which the user's finger is located, typing using this method is time consuming and error-prone. Letters on such keyboards are tiny and are placed too close to one another due to the constrained screen size and so the plethora of touch targets makes typing slow to the point of frustration.

In previous work [26, 7, 23, 76, 56] researchers have tried to tackle this issue by proposing a

set of new input methods, some of which use the Braille alphabet. In most cases, the new method of entering text was compared with a standard QWERTY implementation on a touch screen and found to be superior. However, the various Braille-based input methods have not been compared systematically and empirically so that their individual advantages and disadvantages could be analyzed in detail. In this paper, we put the Braille system of writing under our microscope and ask the question: Given that we have to design a Braille input method, what would be the best way that such a method would be implemented? We do this by proposing a set of four Braille input methods augmented with a small set of editing gestures. We compare our methods along with one existing method from the literature [78] in a usability study.

By testing a set of diverse input methods, we are able to explore the solution space from different angles and elicit different feedback from different groups of users who might be attracted or served best by different methods. Even though this need to cater to the wide diversity of the blind population when typing on a touch screen has been previously recognized in the literature [62], this diversity has not been directly used to guide the design of future input methods. Further, instead of proposing a set of potentially numerous and separate input methods each one to be used by a different group of visually impaired individuals, the current work takes a different approach: We rely on the data collected during our user study to guide us in improving the Braille input method that our users preferred the most.

Previous work [41] has shown that visually impaired users are not as accurate when performing touch gestures compared to sighted individuals. This makes it all the more important that a Braille input method should be able to produce text with as few mistakes as possible while relying on noisy touch input. Also, most visually impaired individuals may employ canes or guide dogs as mobility aids in their everyday life. This makes it hard to touch-type on a mobile phone while one of your hands is otherwise occupied, making the existence of a single handed input method essential. Unlike related research in this area, both of the above factors have been taken into consideration when designing our Braille input methods.

3.1 Problem Description and Motivation

Creating a successful touch keyboard is complicated, as it involves much more than simply drawing a pictorial representation of a physical keyboard on a touch screen. One reason for this extra complexity is that with an on-screen keyboard, users are unable to touch-type like on a physical keyboard. Finding the next character to enter is a more involved mental process, as it requires the visual identification of the target letter before directing a finger to touch it. Compare this to a physical keyboard on which users who have learned to touch-type can locate and acquire letter targets with no conscious effort. Indeed, totally blind individuals can train themselves to become extremely fast typists on a physical keyboard, taking advantage of touch-typing. Similar to sighted typists, experienced blind typists can locate characters on physical keyboards without having to exert any mental effort when locating each key as their fingers "automatically" jump to it. However, given the narrow width of a touch screen and the lack of any physical markings, it is impossible for any user to place all of his/her fingers on a touch keyboard or let alone keep them at a constant and pre-determined location for a long time without drifting, in order to touch-type. Also, since touch screen phones are mobile devices which are most often in use while on the go, one hand is often occupied just by holding the phone and cannot be used for touch-typing. Whilst the lack of a touch-typing ability on touch keyboards is not as detrimental for sighted users typing speed, it can negatively affect the typing rate of blind individuals enormously. This is because without the immediacy of visual feedback, blind individuals are forced to painfully explore the screen by slowly moving a finger over the region surrounding the target letter, until it has finally been located.

Touch keyboards are usually known to suffer from a low hit-rate. This means that once the target character has been located, it is very easy to accidentally tap a nearby character instead of the desired one due to the close proximity of the touch targets on the seemingly tiny phone screen. This issue, which affects both sighted and visually impaired users of touch keyboards, can be more aggravating to the latter group though, who after mistakenly activating a nearby character and after lifting their fingers from the screen, need to repeat the agonizingly slow exploration again from the beginning in order to find and acquire the correct character.

To compensate for the above problems of the lack of touch-typing and of the low hit-rate on

touch keyboards, software developers have added extra algorithmic sophistication which can predict what users are intending to type from what they actually type. These prediction algorithms can then auto-correct on the fly the users erroneous virtual key touches and output the text that most closely matches the users intentions, as they have been perceived by the algorithm. These auto-correcting features of touch keyboards though, might be disabled by blind or visually impaired users, as they often require the user to make a choice between different suggestions of corrected text while typing. These suggestions can interrupt the normal flow of selecting and activating character targets or may appear at unexpected times, confusing the visually impaired user who is forced to listen more carefully to the speech output from his/her mobile phone in order to identify their arrival. Indeed, similar to the fact that sighted users must continuously glance at the phones screen while typing on a touch keyboard, visually impaired individuals need to continuously and attentively listen to the phones screen reader when entering text. Paying attention to the phones synthetic speech output is vital as screen readers are often programmed to echo each individual character and/or word typed enabling the visually impaired user to verify the correctness of his/her input. This need forces especially blind individuals to have to continuously hold the phone close to their heads, in order to use the touch keyboard while being present in a noisy environment or simply in order to maintain their confidentiality. For example, sending a text message during a meeting might need to be done quietly and discreetly, i.e. with limited intrusions by the phone's screen reader and without having to extensively expose the phone into view. A more intuitive method of entering text is therefore essential in order to ease the above pain-points experienced by such users.

A possible solution to the challenge posed to the blind community by the inability to efficiently type on touch screen phones can be the use of a new input method based on the Braille alphabet. The Braille system of writing represents each letter or numeral as one or more Braille cells. Each Braille cell is a pattern made up from a possible set of six dots all of which appear at very specific cell locations. This makes the number of the possible touch targets extremely small and their placement very predictable compared to a touch keyboard. Similarly, the six Braille dots appear in two columns of three dots each, an arrangement which, compared to the proximity of the virtual keys on the touch keyboard, makes it much harder to accidentally touch the wrong target. Figuring out the most preferred approach of entering Braille on a touch screen can be a

challenge of its own though. Obviously, the proposed Braille method should be fast to use and at least easy to adapt to for a person who is familiar with Braille. However, the proposed Braille input method should also prevent the user from making mistakes through spurious or accidental touches, should keep as few of the users fingers as possible occupied to enable comfortably holding the device while on the move and should permit the user to effortlessly type without having to continuously hold the phone close to his/her ear in order to verify every action taken. In fact, it would be ideal if such an input method would, with practice, become second-hand nature to the user, who would then enter text without having to continuously maintain a heightened level attention, similar to the automatized manner in which other daily tasks, such as driving, are performed.

3.2 The Challenge of Using a Touch Screen as an Input Device

Having decided on developing a Braille input method, we have to now discuss how we can use effectively the only relevant input device available to us on modern mobile phones, i.e. the touch screen. Since the early days of the availability of touch screens, there have been efforts to make it accessible to visually impaired individuals. Turning a device which was visual in nature into a tool that the blind community could also use has been, and still is, a challenging riddle for the research community and the industry alike. In general, when attempting to make the touch screens available on modern smart phones accessible, four distinct approaches of finding and activating user interface elements have been proposed:

1. Linearly move amongst items one by one, where a set of simple swipe gestures are used to move a virtual cursor through the applications UI elements in the order they appear on screen. This is one of the techniques employed on the iPhone [33] and although a potentially time consuming method on screens with many items, it is very simple to perform. It can also be easily adapted to most application interaction scenarios. In addition, navigating the user interface linearly is the preferred method employed by the visually impaired when interacting with a desktop computer. One way of possibly implementing our Braille input

method could be to have the user move through the six dots and choose the ones required for each Braille pattern that the user wishes to enter. Repeating this procedure for every Braille pattern to be entered though, would be extremely tedious and thus undesirable.

2. Use parts of the screen as special hot regions, where usually the screen corners are designated as having a special meaning. These hot regions are usually chosen to be easy to memorize or are marked by a tactile sign. The screen corners are especially preferred as that they can be located by blind individuals quickly and reliably [41]. By tapping or double-tapping these special screen regions in a specific order, different commands are performed. For example, on some ATM machines tapping the bottom-left corner of the touch screen moves a virtual cursor to the next on-screen UI element, whilst tapping the bottom-right corner activates the current item. The Mobile Speak screen reader [15] employs this approach. Even though this method is simple to learn and operate, it would seem that the full potential of using a touch screen is not realized as most of its surface area would be unused. When using this approach for our Braille input method, the designated hot regions act as simple virtual buttons and the potential of having rich spatial interactions as afforded by the presence of the touch screen is ignored.

3. Allow the user to explore the screen, reading each UI element as the user's finger moves over it and providing a different gesture for activating the touched element. This is an easy to implement approach which is currently used by the iPhone among other devices. However, exploring the screen can be extremely slow, especially if there are no auditory guides to help you locate the numerous UI elements scattered around it. In a recent study [40], this challenge of searching among a great number of targets became particularly evident as researchers tried to tackle the inaccessibility which still plagues large touch screens such as those used at public kiosks. However, given that our Braille input method would require only 6 items each one representing each Braille dot to be present on screen, an implementation based on screen exploration might be viable.

4. Use specialized gestures for different commands, where a different single or multitouch gesture is assigned to a different command in the user interface. This technique would allow for a rich repertoire of gesture interactions but at the cost of a steeper learning curve.

However, starting from the premise that the Braille Alphabet is a familiar form of written communication within the visually impaired community, the above learning curve should be minimal. Although blind users are able to perform more complicated gestures than sighted users [41], their accuracy suffers. This is because such individuals prefer a guide (screen edge) or an immovable starting-point (screen corner) to be part of the gesture. Entering Braille, however, should not be time-consuming and so our Braille system should pick simple and intuitive gestures involving at most two fingers.

Given the above analysis, it might be beneficial to design a set of Braille input methods each of which would take advantage of a different touch interaction approach. In this work [65], we design one Braille input method which takes advantage of the spatial placement of Braille dots, another which emphasizes screen exploration and two which use intuitive gestures to enter each row of a Braille cell. A method which relies on the ability of the touch screen to be used spatially would permit us to effectively make use of the total surface area available to us on this input device. It would also appeal to blind users' familiarity with Braille, as it would provide a one-to-one mapping between each Braille pattern and the way that it is input. On the other hand, methods which employ a set of simple stationary gestures can be more robust as such gestures can be readily distinguished from one another regardless of the phone's orientation, making the margin of error really small. Additionally, a method which encourages painless exploration of the screen would enable users to learn the system more easily, as well as allowing them to ensure that their input is correct before being submitted, preventing an unnecessary type/undo cycle. Ultimately, the different interaction approaches, including the emphasis each one gives to a different design tenant, i.e. familiarity, robustness and painless screen exploration [7], are compared against one another in a user study.

3.3 Previous Work

A variety of mechanical devices featuring physical keyboards have been employed for typing Braille over the years and in different parts of the world. Most of these keyboards make use of the technique of cording, whereby the user presses one or more keys at the same time to create a Braille pattern. The use of the same technique for typing using the Braille alphabet

has previously been proposed in [12], where a pair of specialized gloves were used as the input device to the computer. These gloves were equipped with a set of special regions under each finger, which were made up of a pressure-sensitive material, each one acting as a virtual key. By applying pressure to one or more of these regions at the same time, all the dot combinations making up the Braille Alphabet could be entered. However, as designed, the material making up these pressure-sensitive regions made the gloves relatively bulky [12].

Instead of using a specialized input device, the use of various forms of stylus strokes or gestures for writing text on a touch screen was explored in [82, 72]. In [82], each letter was represented with a set of Graffiti-based strokes, which the users were required to learn. To ease the learning process, the strokes making up each letter were made to resemble the general shape of the letter itself, but were drawn using only straight lines and in a manner similar to a geometric shape. In the Quikwrite system [72], groups of different letters of the alphabet were separated into different screen regions. Users had to first select the group containing the desired letter and then choose the actual letter from that group. However, both of the above stroke-based techniques either require the blind individual to learn the shape of the actual print letters or to quickly navigate a possibly crowded screen and find precise targets. It is unlikely that most totally blind people will have learned the shapes of the letters of the English alphabet while at school and attempts to entice them to do this just for the use of a novel text-entry system might not bear fruit.

A system using the eight compass directions of North, Northeast, etc., was proposed in [92]. In this system, the user would gesture from the center of an imaginary circle towards any of the eight compass directions in order to select the character which was uniquely mapped onto that direction. Three such imaginary circles of letters where available and the user would switch between them by varying the delay between touching the screen and performing the actual directional gesture. Using gestures instead of having to explore the screen in order to locate and activate specific targets, certainly makes for a friendlier mode of interaction for visually impaired users. However, precisely gesturing towards a very specific direction, especially while being on the move, might be hard as the phone would not be always held with exactly the same orientation. A faster way of switching between the three different circles of letters without having to wait for a pre-determined delay might also be desirable.

The familiarity of most users with the placement of the number keys on a standard telephone

keypad, in addition to the standard association of specific letters to each number, was taken advantage of in [78]. In this work, the touch screen was divided into nine virtual keys, representing the first nine numbers of a telephone keypad. Characters were entered by tapping the virtual key representing the number associated with the desired character multiple times, until the desired character had been selected. Even though the static and well-known positions of the nine numbers on the touch screen made this approach easy to learn, the fact that each number had to be tapped more than once could enable the user's finger to drift, tapping a nearby number accidentally.

Previous attempts have enabled blind users to select letters by moving a virtual cursor around the alphabet [26] or type by selecting letters from eight standard character groupings using a two-level hierarchy [7]. Specifically, a swipe towards the left or towards the right was used in [26] to move a virtual cursor backwards and forwards through all the letters of the alphabet respectively, whilst locating letters faster was accomplished by an upwards or a downwards swipe which would move only among the vowels. However, since words do not usually have letters which are close in alphabetical order to one another, the procedure of having to continuously jump from one place of the alphabet to another would be agonizingly slow. Even the five vowels are not equally spaced out over the alphabet to be used as adequate anchors and so employing the shortcut for moving among the vowels when trying to reach a particular letter might not be sufficient to speed the text-entry process up. The use of a two-level hierarchy for selecting characters was proposed in [7], where the screen was divided into eight segments. Each segment was assigned a list of characters, like the numbers on a telephone keypad. The user could explore the screen using one finger and when a particular segment would be touched, the characters assigned to that segment would be spoken. Touching using a second finger would activate that character group, whereby the user was able to select in a similar manner the desired character from a list arranged alphabetically from the top of the screen downwards. Compared with a direct, spatially-oriented Braille input method, however, a possible weakness with the above method is that the two-level hierarchy coupled with the fact that a split-tap gesture is always needed to select a screen target might unacceptably slow down each character's entry.

In [23, 76] typing Braille on a smart phone's touch screen similar to the way that Braille is entered on a mechanical Brailler was demonstrated. However, this method requires the use of at least three fingers from each hand, making holding the phone with the remaining fingers difficult

and allowing for spurious touches. The use of a set of gestures in order to enter each Braille character row-by-row has been proposed in [56]. Despite the fact that this approach is similar to one of our Braille input methods discussed below 3.4.1, our method is different in the sense that it was designed to be used single-handed, a common usage scenario. Contrary to the method in [56] which includes gestures requiring three fingers, our corresponding method can be used on phones with narrower screens or on phones which do not support more than two simultaneous touches, a limitation which unfortunately is present on various devices.

The diversity of the population of visually impaired users and its effects on the usage of touch screen input methods has been identified in [62]. The authors found that the age, the time of onset of blindness, as well as the cognitive and spatial abilities of the individual can play a role in the speed and accuracy of using various input methods that had been described previously in the literature. However, the authors did not try to design an improved input method but proposed that all text entry methods should be available in order to fulfill the needs of different users. Additionally, the authors did not compare different Braille input techniques in order to discover if the relative slowness determined in the Braille input method they used could be in any way remedied.

In contrast, various Braille input techniques were described in [16]. However, their usage was not thoroughly evaluated and the relationships between the different methods not investigated to the point of deriving guidelines to assist in creating an improved Braille input method. Finally, a common weakness of most of the above solutions is that little emphasis was given on methods for editing or navigating already entered text.

3.4 System Design

This section describes the implementation of the four Braille input methods we have devised. An additional fifth method which is derived from research encountered in the literature [78, 7] and which we have included in our application for comparison purposes is also presented. For all the methods, we detail the complete user experience they offer, i.e. how the user is supposed to interact with each method and how the system responds to the user's touches. For the first of our Braille-based methods, we emphasize the algorithm we developed in order to improve the

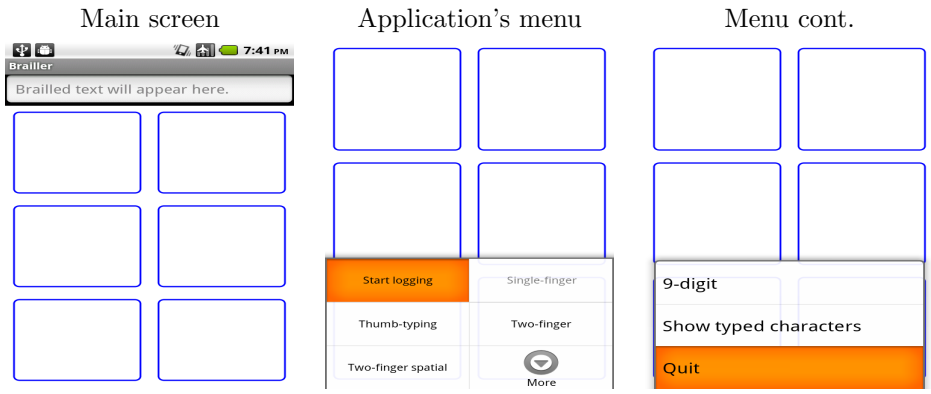


Figure 3.1: Screenshots of interface

accuracy of that particular method. Finally, the editing and navigation gestures available in our Brailler application are described.

3.4.1 A Variety of Input Methods

As already discussed 3.1, instead of having to learn a new system of touches or swipes, our system aims to use the Braille Alphabet, solving the memorization problem of other approaches. In our system the touch screen is used as the surface where Braille characters are entered, making our implementation able to run on most modern smart phones. To permit editing and review of entered text, we have also implemented a set of simple directional gestures which act as the space, backspace and arrow keys.

On initial load, the system shows a Braille cell where dots can be tapped using one finger to form a Braille pattern 3.1. Once touched, Braille patterns are interpreted and the corresponding letter of the English alphabet is typed in a standard text box. To erase a character, the user can swipe left with one finger. Activating the menu offers the user the ability to switch amongst the various ways of entering Braille, such as a thumb-based or a single-handed method, described below. An extra input method which employs the first nine numbers of the telephone keypad is also offered, in addition to the ability to hide the edit box in which the actual characters are typed.

The input methods offered are listed next. As previously discussed 3.2, each one was designed

with a different design tenant in mind.

1. One-Finger: This method was designed with user familiarity in mind. Each Braille dot is selected spatially on a virtual three-by-two grid by tapping. Each time a dot is tapped, the software speaks the dot's number. After a specific short interval has passed without any screen touches, the entered dots are interpreted and the resultant character is typed.

   This method allows the user to effectively "sketch out" the character he or she wishes to enter using Braille. The interval before the entered dots are interpreted is calibrated to be short enough to make this input method appear natural to a blind Braillist, but long enough to allow a character with multiple dots to be entered without mistakes. Even though the dots are placed on a visual grid, our algorithm does not rely on the user having to touch the exact locations where dots are visually present, but can intelligently deduce the entered character by the overall shape of the tapped locations.

   More specifically, when using this method, a depiction of an empty Braille cell appears on the phone's screen and Braille dots light up when touched. This is for the benefit of the partially-sighted. Users are expected to select each dot making up the Braille pattern they desire by touching it. However, after analyzing a set of touches for various Braille patterns 3.2, we realize that touches corresponding to each Braille dot were not always in the designated rectangular region for that dot. This suggested that a better approach of interpreting Braille dots from a list of touch locations should be devised. To fix this, our algorithm tries to find the Braille pattern which most closely resembles the shape of the touch locations. It enumerates all the possible Braille patterns whose dots centers are at the visible predetermined screen locations and finds the one that has the minimum Euclidian distance from all of the touch locations.

2. Split-Tap: This method emphasizes painless exploration of the on-screen content. Each dot is selected spatially as above but not by single taps. Instead the user moves a finger around the screen until he or she hears the desired dot number. Then, the user places a second finger on the screen to select it. After selecting all the dots making up the desired character, the user finishes entering the character by lifting up the first finger. As soon as the finger is lifted, text-to-speech is again used to speak the character just typed.

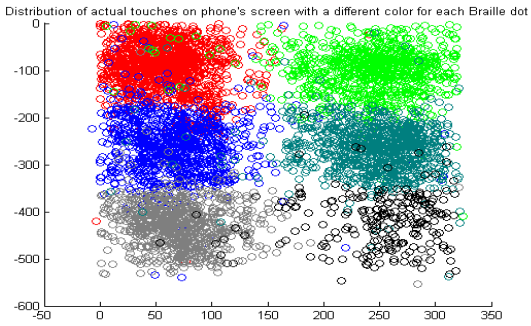


Figure 3.2: Distribution of touches for each dot

By confirming each dot before being selected, this method should also help the user to be more accurate when entering Braille. To achieve this accuracy, however, it is apparent that typing speed is somewhat sacrificed. Ultimately, a user study should decide whether this sacrifice of speed is worth the additional accuracy.

3. Two-Finger: To facilitate single handed text entry, we allow the ability to input a Braille character one row at a time. For each character the user taps each row of the Braille cell individually using the following gestures: If a row contains both dots, then two fingers are tapped. Otherwise the corresponding left or right dots are tapped. If a row has no dots, then a downward gesture is performed with both fingers. The remaining three fingers are used to hold the phone. Before the last row has been entered, the user can swipe upwards using two fingers to a previous row and correct it in case of error. Corrections can be performed using the same gestures for entering dots, which when repeated for a second time on the same row, erase their corresponding dots. After selecting the dots of each row, the system uses text-to-speech to speak out the numbers of the dots selected. Similarly, after erasing a set of dots for a specific row, their numbers are spoken with the word "off" appended to them.

   This method together with the next one were designed in order to enable a more robust text-entry technique, which would not depend on how the user is holding the phone or where exactly the user would have to touch, but on simpler to distinguish touch patterns, such as whether the user is touching with the left or with the right finger.

4. Thumb-Typing: To allow the user to hold the phone more securely with one hand, a method of typing only using the thumb is proposed. Given the popularity of using the thumb by many individuals to type on touch screens, it was hoped that this method would be deemed familiar by most. The Braille pattern is also entered row-by-row as in the previous method. The thumb is tapped in the vicinity of the top-left quadrant of the screen to indicate that the left dot in the current row is selected and it is tapped towards the top-right quadrant to indicate that the right dot is selected. To select both dots in a row, the thumb bends in a natural manner and taps in the bottom-half of the screen. To leave a row empty, the thumb swipes down. Previous rows of the Braille cell could also be revisited and edited by swiping up, as in the previous method.

5. Nine-Digit: We implemented a combination of the methods detailed in [78, 7] but with a slight twist to prevent accidental touches arising out of the need to accurately tap multiple times on a single target. The numbers 1 to 9 with their corresponding letters appear in a standard telephone keypad formation. Instead of the user having to tap a number multiple times in order to get to the desired letter, however, the user chooses first a number and then taps one of its letters from a list arranged horizontally. The user can also explore the positions of the nine numbers and, once a number has been selected, the position of its letters, by moving a finger around the screen without lifting it, similar to the approach adopted in [7]. Once the finger is lifted or a second tap with another finger is performed, the number or character which was last touched is selected.

   Obviously, given the great familiarity of most users with the telephone keypad, the placement of the nine numbers should be predictable. Their locations should be easy to find using the screen's edges and corners as guides. Also, instead of each number occupying a region of screen real-estate commensurate to its shape, the screen is equally divided into nine rectangles and each number can be activated by touching anywhere within its corresponding rectangle. The above design decisions should decrease the need for screen exploration to a minimum. Also, for most numbers which have three corresponding characters, these characters are arranged so that each one virtually takes up an entire column. So, tapping anywhere on the left side of the screen would activate the first character, tapping towards

the middle the second one and touching anywhere close to the right edge of the screen the third. For numbers with more than three characters, the last one takes up the whole of the bottom half of the screen, whilst the top half is divided into three columns as before. This arrangement is very practical as the top half of the screen is easier to reach than the bottom and so mistakenly activating the fourth character should be difficult. In the same manner as in [7], a leftward swipe performed after having selected a number, cancels the selection.

3.4.2 Gestures for Navigation and Editing

Most related work has left the all essential editing functionality out of their implementations. In contrast, we have defined four directional swipes which can be used as follows: For all methods, a space character can be entered using a rightward swipe, whilst a leftward one is used for backspace. Similarly, moving the editing cursor left and right character-by-character through the entered text is enabled by swiping upwards and downwards respectively, except when using the Thumb-Typing method, where a two-finger up and down swipe is used instead. While moving the cursor, the letter to the right of the cursor is always spoken. When the backspace gesture is performed, the character being erased is also announced, but in a higher pitch.

3.5 Evaluating the System through a User Study

3.5.1 Study Design and Evaluation Methodology

Many attempts at designing new input methods have tried to evaluate their design choices only through the use of relatively dry metrics such as typing accuracy and speed. Even though we take such quantitative measurements into consideration and whilst they are important as an overall evaluation of the text-entry system, we feel that they cannot tell the whole story as it is hard to derive the causes which are responsible for producing them. Research studies concentrating on these metrics do not find enough time to present many alternative prototype implementations to users simultaneously, so as to permit them to compare and contrast amongst an array of choices at once.

In this work, we carried out a user study which included 15 visually impaired participants from the greater New York City area 3.1. The software was tested on an Android-based phone. For each of the participants, we gave them a short training time to familiarize themselves with each input method. This training phase could include a description of each input technique, its various gestures and idiosyncrasies, such as a listing of the dot locations which could be tapped and the expected verbal announcements that would be heard. Not all users managed to complete this training for all five input methods. Some users who required more training would be asked to enter some letters of the English alphabet, or some short words if necessary, in order to familiarize themselves with the input method being tested. After the training phase, we told our users that we would begin recording their touches and their entered text in order to discover any shortcomings and bugs of the system, and not in order to evaluate their own typing skills. The subjects were then given randomly chosen phrases from a standard phrase set, which they were asked to type. The users were asked to answer a questionnaire with the same quantitative and open-ended questions for each input method. The quantitative questions asked the users to rate on a scale of 1 to 4 how easy each method was to use, how easy it was to learn, and how likely they would be to use it in the future. The open-ended questions prompted the users to give more details about what they liked and disliked about each method and their responses were recorded verbatim. At the end of each session, the person conducting the interview would enter detailed notes on what was deduced from the participant's expressed feelings and thought processes when employing the system. For example, any difficulties that the user had encountered in understanding and using each method would be described, in addition to any suggestions on how such difficulties arose and how they should be overcome.

As can be seen from the above protocol, during our user study, we engaged our participants into a verbal dialog, in addition to collecting standard touch and timing log data. As a result, we do not only passively witness the outcome of testing our different input methods, but we also try to glean the reasons behind the participants actions, exposing their underlining mental processes.

Our age representation appears to include both younger and older individuals. Around two thirds of our participants were totally blind whilst the rest were legally blind. The group of totally blind persons includes some users who had extremely limited vision, e.g. they could see

Characteristic	Yes	No
Age < 50?	6	9
Totally blind?	11	4
Blind since birth?	7	8
Uses touch screen phone?	7	8
Uses screen reader on phone?	8	7
Knows Braille well?	12	3

Table 3.1: The user participants

light direction or some shadows, but who could not make any use of such vision in any way. Also, persons with blindness only in one eye but with total vision in the other were not considered to be visually impaired. We observe that all of our participants have used at least a phone with a numeric keypad, even though three of them are using it without any accessibility support at all. Around half of our participants have experience with a touch screen phone and almost an equal number have used a dedicated mobile screen reader. What was surprising was that around the remaining half of our participants had only used the basic built-in text-to-speech support that comes with some phones. This support is very limited and is usually provided in order to assist hands-free driving and, in general, is not present for the benefit of visually impaired users.

3.5.2 Study Results

In this section, the overall usefulness of each of the five input methods as expressed by our study participants and their suggestions for improvements are listed. From the results, the One-Finger method comes out to be the most preferred and the simplest to learn; whilst some often voiced requests concerned the support of abbreviated (Grade Two) Braille and of more advanced editing commands. In addition to categorizing and detailing the users' feedback for each input method, we try to give an overview of the perceptions of our users by dividing them into two groups representing separate attitude trends and evaluate how these trends match with our original design tenants 3.2 of familiarity, robustness and painless exploration.

Generally, almost all of the participants who owned a touch screen phone found our system to

be easier, more intuitive and more desirable for them to use than their phones' touch keyboard. Those participants who did not know Braille very well considered our system to be an excellent vehicle through which they could learn it quickly.

"I did not need to go around searching for the letter like with QUERTY touch keyboard."

"I liked it because it was interesting for me to learn something new. (Meaning to learn Braille.) I thought Braille was very complicated but it is not."

None of the participants said though that entering Braille using a touch screen would be more desirable than using a device with physical buttons. However, given the current hardware trends, such devices would be all the more difficult to find in the market.

"I think having keys and buttons, something that you can feel would be easier."

Comparing Amongst Input Methods

The One-Finger method was judged to be the simplest, the most intuitive and the most preferred, followed by the Nine-Digit method. The One-Finger method was described as very natural and requiring no training, whilst a negative aspect of the Nine-Digit method was the difficulty of its two-step process for letter selection.

An isolated group of users enjoyed the Two-Finger method very much and believed that it was a clever idea. However, most disliked its row-by-row input and the way it forced you to hold the phone, a result that we personally found very surprising. The Split-Tap method was perceived as being more accurate but much slower, causing frustration. The Thumb-Typing method was generally not understood or its gestures were found to be hard to perform.

On a scale of 1 to 4, the following table 3.2 lists the mean and standard deviations for each rating across each input method:

For the One-Finger method, there appears to be a correlation between the user's age and the average typing speed for each Braille pattern 3.3. Older users complete Braille patterns faster than younger ones. This indicates that a possible improvement to the One-Finger method would be to dynamically adjust the algorithmic parameters (such as the interpretation delay) to accommodate different ages.

Method	Easy to learn	Likely to use
One-Finger (n=15)	3.6 ± 0.63	3.53 ± 0.92
Split-Tap (n=12)	3.17 ± 0.72	2.75 ± 0.97
Two-Finger (n=12)	2.58 ± 1	2.5 ± 1
Thumb-Typing (n=6)	2 ± 1.26	1.83 ± 1.33
Nine-Digit (n=15)	3.067 ± 0.97	2.47 ± 1.13

Table 3.2: User ratings of input methods

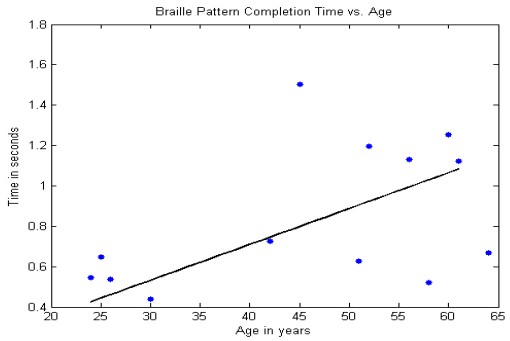


Figure 3.3: Completion time increases with age

Comparing Between User Groups

Our user participants can be roughly divided into some general categories based on their general inclinations when using the system:

1. Six totally blind users who know Braille very well and use it, but who had no experience using smart phones or phones with a touch screen. They only know how to place or answer calls on phones with a numeric keypad but they do not use any screen reader or their experiences with one were less than satisfactory. They are thus unable to read text messages. They include both younger as well as older individuals. Also, they seem to be attracted to our Braille system, i.e. they find it "interesting", due to some sentimental attachment with the Braille system of writing in general.

2. Eight users of varying ages who are either totally blind or legally blind and who have enough familiarity or own a touch screen phone, most times the iPhone. Some of these users might be excellent Braille readers whilst others might read Braille but slowly.

3. One user who falls into neither of the above categories, since this user neither knows Braille well nor owns a touch screen phone.

The two main groups can be called the Braillists and the Technologists. The Braillists are strong proponents of the Braille system of writing, they have been using Braille continuously since many years for their daily needs. They enjoy getting their information in a tactile manner and are not so much into text-to-speech or electronic technologies. On the contrary, the Technologists are not so dependent on Braille and own or are in the process of learning how to use a touch screen phone. They rely more on mainstream gadgets or software for their daily needs of communication and information. After carefully looking through their questionnaire responses, for the Braillists, familiarity was the key design tenant for a successful text input method, followed by robustness. For the technologists, robustness was more important than familiarity, as to them it signified a well-written piece of software which they felt eager to explore. However, the possible robustness offered by the Two-Finger method was outweighed by its relative complexity and slowness. It is no wonder, therefore, that after all factors had been considered, most users of both groups preferred the familiarity offered by the One-Finger method, coupled with

the robustness ensured by its pattern-matching algorithm, which allowed for inaccurate touches. In contrast to our expectations, the painless exploration afforded by the Split-Tap method was found to be unnecessary and even frustrating by experienced and beginners alike.

3.6 Discussion

The One-Finger method received the highest ratings because the users who knew Braille could grasp how it worked very quickly. Some of them even became comfortably proficient using it after less than an hour. Unlike the Two-Finger or the Thumb-Typing methods, which required a higher cognitive load and a longer learning curve, the One-Finger method proved to be a more natural way of entering Braille. Similarly, the Nine-Digit method, despite its familiar numpad design, proved somewhat less desirable compared to One-Finger due to its two-level hierarchy.

Even when using the One-Finger method though, many users took exception with the length of the interval before the entered pattern was interpreted. A group of users wanted the interval to be adjustable either manually based on their skill-level, or, automatically by a heuristic depending on the physical characteristics of their touches, such as their pressure or their ordering. This strongly suggests that fixed delays in a UI are annoying to users, as some of them would find them too short, whilst others too long. Clearly, concerning the One-Finger method, the interpretation interval needs to adapt to users' typing speed and currently entered Braille pattern.

Concerning the benefits of the Split-Tap method, it was clear that specific users wanted to be able to cancel erroneously entered dots before completing the whole Braille pattern, whilst others wanted to be able to confirm each dot pressed. They felt that waiting until the whole pattern has been entered and interpreted, just to be subsequently able to delete it, was a waste of time. In spite of this, using the Split-Tap method for this purpose was deemed undesirable as many participants rejected the split-tap gesture as too slow and cumbersome, whilst some found the whole Split-Tap method as too hard to learn. Performing this gesture while the first finger was towards the edges of the screen felt awkward, whilst the second tap would at times make some users accidentally lift up the first finger, registering the wrong Braille pattern. This indicates that for text entry input methods, the split-tap gesture might be inappropriate and should be avoided.

Nevertheless, some form of input verification appears necessary, as some participants would continuously use backspace to ensure themselves that they had correctly typed something or in order to check their progress in the text. Ultimately, the participants wanted to have the ability that the Split-Tap method offers to confirm each Braille dot, but without having to perform a slow split-tap gesture each time. Designing such a method though would be hard, as using, for example, a double-tap gesture for confirming each dot, might turn a cumbersome method into an even more cumbersome one. At the end of the day, the seemingly simplistic One-Finger method offered a compromise for these users needs, as its pattern-matching algorithm would automatically compensate their desire for higher accuracy.

Most participants who knew Braille would conceptualize each Braille cell in terms of two columns of three dots. They had a hard time adapting to the row by row separation of the Two-Finger method, including those users who had enough vision. The widely known numerical ordering of the dots, which places dots $1-3$ on the left column and dots $4-6$ on a second column, seems to be creating this problem. Even users who understood the Two-Finger method conceptually, still had trouble switching to a different dot ordering required by the Two-Finger method. However, the few participants who familiarized themselves with this method quickly, found it extremely preferable. This indicates that training is needed for mastering this method but once learned the method might prove very useful. For this possibly laborious training to be undertaken by the user though, a sufficient motive should be present. The benefits of the input method, such as providing one-handed input or an enjoyable game-like approach of teaching yourself Braille, should outweigh the effort involved.

A part of our design which might need improvement is the fact that a cursor was not showing up on the screen when using the system. Users who relied on some limited form of vision could not tell their location easily by listening only to a stream of letters that were passed over when using the virtual cursor. However, showing a text box with the cursor was considered and tried. It was found to take up important screen real-estate and make totally blind users tap it accidentally. As a result, it was hidden by default with the option to turn it back on if required.

3.7 Future Work

One user wisely mentioned: "I would think that the letters would start on the left. They should work in a motion from left to right." Taking this comment into consideration, We should change the pattern matching algorithm so that between competing choices of letters, it would prefer those that have patterns which, when tapped from left to right and from top to bottom more closely resemble the entered pattern. In other words, make the ordering of the user taps influence the decision of the matching algorithm.

For all the methods we should add a filter which will use the pressure of the touch to determine whether it was an accidental or an intentional touch. Also, for some of the methods, touching with more than one finger and for all the methods double-tapping is not a valid gesture. We should write filters for each method which would remove such invalid accidental touches in order to assist users like some participants who did not have the best finger dexterity. To fix this we should make the software ignore extra touches when the One Finger method is used. Additionally, users would accidentally tap the same dot more than once without realizing it. Given this, our system should ignore multiple taps at the same dot for this input method since there would be no valid Braille pattern which can have one dot pressed twice.

With users who are relatively advanced, their extra confidence would sometimes, especially for characters with few dots, work against them. It would make them forget to wait for the entered dots to be interpreted and they would get two patterns of neighboring characters mixed together. On the contrary, when a character had too many dots, the interpretation interval would sometimes prove to be too short for them, making the system erroneously break up an entered pattern into many characters. During the study, an inside on how to tackle this problem came from another user who gave the One-Finger method a lower score than his successful experience using it would suggest. This is because of the lack of mastery he felt due to the issues with the interpretation time-out. He said that he wanted to type as fast or as slow as he wanted to and that the delay made him lose this control over the software. As a result, an adjustable interval based on the length of the entered pattern or based on the speed that dots are entered should be implemented. When a pattern has more dots, the interval should lengthen to give you extra time to move around the screen and mentally construct the complex pattern. Similarly, when the dots

are typed with a faster speed, the interval should shorten itself, to allow for a more experienced user to complete what he/she is typing without frustration.

Another issue was that users were confused about the maximum height of the input view as they would originally think that it did not span the whole of the screen but that it only took up the top part of it. This is because the bottom row of the screen was taken up by the Android's default buttons, a fact that made most users feel uncomfortable and lose the sense of boundaries. Removing these buttons, therefore, should be a top priority, whilst dynamically resizing the typing view based on the user's preferred touch area and touch history should also be considered.

A few users would have desired a more tactile or more personalized set of boundaries than the current set which were roughly the physical edges of the screen. The current reliance on the physical screen edges is corroborated by the findings in [41] where it was shown that screen edges are a site where most visually impaired users perform most of their gestures. From the interviews as well as the recorded touch data, it is apparent that most visually impaired users would be better served by an auditory guide which would help them identify the boundaries of the application's typing area and the size of the area occupied by each Braille dot. Otherwise some would accidentally activate extraneous UI elements or lose their orientation.

Most users, when trying to perform a swipe gesture, accidentally do not swipe as fast causing the screen exploration feature to be activated instead. Taking this into account, we should add sounds that would indicate that you are exploring the screen, like those present on the iPhone, which would make it clear when someone is exploring and when they are swiping. This will "teach" the users what the correct speed sensitivity is.

A top request for us was to implement the full set of the Braille writing system, i.e. abbreviated Braille, symbols and Mathematics. Also, many users wanted to be able to control the amount of information spoken or have additional speech commands, such as to echo each word upon completion. Adding extra configuration options to our software, however, should be carefully balanced against the need to maintain intuitiveness, namely that our system should continue to be easy to learn. Lastly, the need for more editing gestures, such as a Clear All gesture, was brought up by some of the participants.

3.8 Summary

We have proposed four Braille-based text-entry techniques which use the Braille alphabet, one of which minimizes mistakes through pattern matching of user touches and all of which provide easy editing through swipe-based cursor manipulations. We have evaluated our system through a user study which compares our input methods with one another, as well as with an existing numpad-based technique. We have found that a balanced approach provided by the One-Finger method which combines ease of use with a relatively good accuracy is most preferable. Other methods, which either enable a faster typing speed but impose more complicated gestures (Two-Finger method) or provide the ability to confirm each dot entered but are slower (Split-Tap method), are too cumbersome to be useful.

As future work, we plan to improve the One-Finger method to make it more resilient to noisy touches and more adaptive to users' spatial idiosyncrasies. To achieve this, we are planning to use an adjustable interpretation interval based both on the length of the entered pattern and on the speed that dots are entered. We also plan to improve the method's robustness by dynamically re-locating the position of each Braille dot away from the current symmetric layout, depending on the spatial concentration of each user's touches.

Chapter 4

Exchanging Banknotes without Fear: A Mobile Tool for Reliable Cash Identification

The ability to correctly and effortlessly exchange cash is fundamental for our everyday needs. Many simple transactions which are conducted each day, such as buying groceries or dining at a restaurant, require not only the handing over of paper bills but, more often than not, the return of some change. Unfortunately, in certain countries, visually impaired individuals cannot distinguish banknotes of different denominations from one another. In the United States, for example, dollar bills of different denominations all have the same size, shape, texture and color. This has been a source of anguish for the visually impaired community, sparking a successful lawsuit against the government of the United State [37].

Visually impaired people are dependent on the good will, the honesty and kindness of others to help them organize and recognize their banknotes. Given the central role that money and more specifically cash plays in our social and professional lives, this dependence on others places the visually impaired at a stark disadvantage. To overcome this dependence, the visually impaired have come up with various forms of coping methods which can help them, to an extent, deal with

the situation. These practical but often fragile methods include folding some bills in their wallets while keeping those of other denominations straight, or even storing different denominations in different pockets. These procedures are easy to mix up and forget, given that they must be performed with great detail and care every time a new banknote has been received. Relying on the assistance of others when using inaccessible currencies has become therefore a fact of life for most visually impaired individuals, robbing them of their independence.

The popularity of smart phones with built-in high-resolution cameras can provide a possible solution to the currency recognition problem. In this work [67, 64] we propose a software system which runs on a smart phone and employs the phone's camera to take a continuous stream of images of the object placed in front of it. This software analyzes the provided images and determines whether they depict a dollar bill. If so, the software recognizes the denomination of the banknote. It subsequently uses synthetic speech to announce the results of its recognition. The software employs the Scale Invariant Feature Transform (SIFT) [54] for feature extraction but a faster approach for feature classification so that it can work effectively on the mobile phone. We evaluated our algorithm using real pictures of bills taken by a visually impaired user through the phone's camera.

4.1 Problem Description and Motivation

This section explains in more detail the everyday problem that visually impaired users in some countries face when handling banknotes. It then outlines the practical challenges that arise when trying to develop a piece of mobile phone software for identifying such paper currency.

4.1.1 Practical Challenges when Using Paper Bills

In the United States, dollar bills of different denominations all have the same size and so cannot be easily separated by measuring or comparing one against another. To make things worse, there are no tactile markings or other forms of identification on each bill to enable a blind person to discover its value without any sighted assistance. The various engravings or embossed pictures currently found on such paper bills are too thin and lightweight to be felt by the sense of touch. As a Federal court noted, "it can no longer be successfully argued that a blind person has 'meaningful

access' to currency if she cannot accurately identify paper money without assistance", [37].

In 120 other countries, including the countries which have adopted the Euro, paper currency comes in different sizes, [87]. However, in the European Union, despite the fact that Euro bills of larger denominations have larger sizes, it might still not be easy to separate them quickly and effortlessly. Comparing several Euro bills in your hand against one another takes time especially if a person has low finger dexterity, a difficulty faced by many seniors which are a group representing the majority of visually impaired individuals, [20]. Also, the difference between the sizes of these Euro bills might not be as drastic as some individuals would have required. The difference in width between a 5 Euro bill, for example, which is the smallest in denomination, and a 500 Euro bill, which is the largest, is only 2 centimeters, [87].

According to [87], paper bills of different denominations around the world do not differ only in size, but in many countries they also differ by color and tactile markings. Very large numerals are used in order to assist the partially sighted and certain other population groups whose sight is diminishing. Using more distinctive colors or larger numerals, however, cannot certainly be of any use to the totally blind. Countries which have used tactile markings have discovered that such markings disappear after bills have been in circulation for a while as they tend to wear out with time and the extensive usage of the bill. Employing a pattern of distinctive holes or cut corners is undesirable, as this could lessen the lifetime of the bill by allowing it to be more easily torn. Even though electronic devices which can identify dollar bills are available on the market, these devices can cost up to $300 and are not always accurate, especially with older or worn out bills. Meanwhile, visually impaired individuals do not want to carry around with them yet another specialized gadget just to help them distinguish their paper currency.

While credit cards and other forms of electronic payment are gaining popularity, paper currency is still widely used, [87], especially for transactions of smaller value. People still carry cash in their pockets alongside their credit cards, whilst the various efforts to create an electronic software-based wallet have still to gain any widespread traction. This preference for paper currency is understandable due to the perceived security, the simplicity and above all the anonymity that it offers. Unlike other currently available forms of payment, cash is accepted everywhere and it does not require an electronic connection to any financial network to be valid, whilst using it does not necessitate giving away any personal information, such as your name.

The inability to recognize bills exposes blind individuals to fraud as, for example, it can enable unscrupulous sellers to hand bills to visually impaired buyers which have much less value than the correct amount. Such forms of cheating may never be discovered or may be discovered too late by the visually impaired victim for him or her to be able to take any appropriate action.

4.1.2 Algorithmic Challenges

The reliance of the visually impaired on the assistance of their sighted friends or even on the untrusted assistance of strangers when handling banknotes, cannot be replaced with a piece of software which will either work on half of the bills or which will assign the wrong denominations to banknotes. When waiting to pay on a busy line, the visually impaired users should not be expected to have to spend a long amount of time for the mobile phone software to be able to recognize each dollar bill. In addition, other irrelevant objects which happen to be captured should not be identified as banknotes. Identifying banknotes using mobile phone software can be, therefore, algorithmically challenging as such software requires a high accuracy and speed. This extra speed is not guaranteed to be available on a mobile phone given that most advanced image feature extraction algorithms are computationally hungry.

When a blind user wants to find out the value of a particular piece of currency, he or she will not be aware of the intensity or even of the availability of a suitable light source. So, the software should work under various and even under difficult lighting conditions. Similarly, one cannot expect a visually impaired individual to place the banknote straight in front of the phone's camera, removing any other objects, such as furniture, which might happen to be in the background. No assumptions could be made about which face of the bill would be pointed towards the camera, or that a specific background, such as a white-colored table surface, would always be used.

A blind person might not even know the exact location of the camera's lens and so might inadvertently position a finger or another protrusion in between the phone and the banknote. It would be an inconvenience for the user to have to unfold each banknote and position it in a very specific orientation or with a specific face pointing towards the phone. In fact, the user would most probably present banknotes to the system which would be folded, rotated with various

angles and at various distances from the camera's lens.

Pictures taken by a visually impaired user might be blurred. This is because, the quality of the pictures gathered from mobile devices can be highly variable. Some images may be so blurred that even human recognition would be hard.

In summary, a successful currency recognition algorithm needs to work accurately under various lighting conditions and even when bills are folded or covered by fingers, i.e. under partial occlusion, whilst banknotes need to be identified from several angles and distances.

4.2 Related Work

Previous attempts [52, 51, 69, 71] have used very specific and specialized techniques when tackling the problem of unhindered access to paper currency. However, any specialized technique can be fragile and hard to port from one type of currency to another. In addition, such techniques suffer from the fact that they do not take advantage of the vast research in image feature extraction that took place in the field of computer vision in the last years.

The AdaBoost learning algorithm was used in [52, 51], to train a set of weak classifiers in order to determine the value of dollar bills. These weak classifiers consisted of a set of specific pixel pairs on each bill which were picked by the researchers. However, even though this system works on both faces of the bill, it seems that it still requires the particular face to be exposed fully to the camera and so would not work on folded bills or bills with distortion. The blind user would still need to orient each bill and take care where the phone's camera was being pointed, a procedure hard to perform when standing in line at a store. In comparison to a robust and well established image recognition algorithm which can reliably extract distinguishing features from any image presented, the authors' procedure of selecting numerous distinct pixel pairs for each bill cannot easily scale, especially when having to port the system to more currencies of other countries.

Similarly, in [71], specific regions which contain "characteristic saliencies that differ enough from one bill to the other" were selected. These characteristic image regions were also rotated in order to create more training samples which were then fed to an image recognition algorithm. However, although identifying bills under multiple orientations is very useful to a visually im-

paired individual, the distinguishing regions for each bill are still picked by hand and do not cover the whole of the bill's surface. In fact, users of the system had to first locate the plastic strip on each bill before taking a picture of that specific area in order that the recognition would work.

The idea of finding specific unique characteristics which could easily separate one banknote from another was taken a step further in [69]. The authors employed an algorithm which would help the user move the bill until the denomination's value printed on it would be exposed to the camera. Asking the user to move the banknote around until a region of interest has been located, however, can be tedious and time consuming.

Using real humans as a part of the image recognition process was proposed in [90]. In this work, images are first labeled by using an automatic approach such as a database or an image search engine and the results are validated in a distributed manner by paid human workers through Amazon Mechanical Turk. This system can certainly be adapted and used by the visually impaired to identify their banknotes. However, the use of human workers means that the users would need to incur at least some financial cost, a fact which can be avoided by building a completely automatic and high-accuracy currency recognition system which could also run without any connection to an online service.

4.3 System Design

Our system works by using a set of sample images of dollar bills which are used to train a set of classification algorithms outlined below 4.3.3. The system parameters are not tuned manually and it does not rely on any hand-picked distinguishing visual characteristics of bills. Instead a more robust machine learning approach is followed whereby the training data is used to guide the algorithm in recognizing similar bills when they are later presented to it by the visually impaired user.

In this section we describe the algorithms used in our system and our efforts to improve both the accuracy as well as the efficiency of these algorithms so that they can successfully run on a mobile phone. We also list all the methods we experimented with, but which were found to yield low accuracy during this process. The ultimate performance benefits of each of these methods

are listed in the next section 4.4.2. First we outline how we pre-process our image samples before extracting SIFT key-points 4.3.1. This is followed by an explanation of the methods we employ to encode and aggregate the key-points into feature vectors describing each image 4.3.2. Finally, we detail the classification algorithms 4.3.3 we employ on the computed features in order to identify the denomination of unseen bills, including how we determine if an object is a bill or not 4.3.4.

4.3.1 Image Pre-Processing

Our system stores and uses an array of training images for each supported denomination, ($1, $5, $10 and $20), the collection methodology of which is described in section 4.4.1. Pictures of the bills to be recognized (the testing data) are captured by a visually impaired user. Each image is resized to a height of 300 pixels and its width is proportionally scaled. A 200 pixel white border is added around the image. The effects of the color of the lighting source on the images are removed using the Gray World Assumption 4.3.1 and each image is turned into grayscale. For experimentation and to account for image distortions, we optionally create additional artificial training images by taking the existing images and rotating them through 90, 180 and 270 degrees, in addition to scaling each one by 0.5 and by 1.5. Finally, an implementation of the SIFT algorithm is used to extract a collection of key-points for each of the training images 4.3.1.

Fixing Lighting with The Gray World Assumption

As outlined in section 4.1.2, blind users cannot be expected to adjust in any way or even be aware of the light source available in their environment. However, images captured under lights with different colors will look much different from one another. Any sample images use to train our currency recognition algorithm would appear dissimilar from the test samples of the same denomination, making recognition difficult. This problem whereby the color of the light source affects the captured image can be remedied using color-balancing algorithms. One such balancing algorithm uses the Gray World Assumption to remove the effects of the light source, [18]. This assumption is based on the fact that in any realistic and thus sufficiently diverse scene, we expect to have a diverse amount of colors and color differences. At a very high and simplistic level, one could even assume that this variety in colors may average out to the color gray.

In our system, we employ the Gray World Assumption on all our banknote images. The mean value of each red/green/blue (RGB) color component is computed over all the pixels of each image. These mean values should be equivalent to the values of a uniform gray color for the image under normal lighting conditions, if the Gray World Assumption holds. A common gray color for each image is computed by taking the average of the 3 RGB mean values. The value for the gray color for each image is divided by the mean values for the RGB components computed above to create a scaling factor for each color component. All pixels are then adjusted by multiplying each of their color components with the corresponding scaling factor. As a result, each component is adjusted based on the amount of deviation from the common gray color for that image.

Employing the SIFT Algorithm

We employ an adaptation of the Scale Invariant Feature Transform (SIFT) algorithm [54] which is widely used in the vision community for detecting similarities across images. The SIFT algorithm identifies *key-points* or *descriptors* within any image and generates a multi-dimensional feature vector representation of each key-point. SIFT is an ideal choice since it can be used to perform robust classification in the face of positional, rotational and scale variants.

Normalization of SIFT Key-Points

Since some classification algorithms expect input features to be scaled similarly, we normalized SIFT key-point dimensions by subtracting their mean and dividing by their standard deviation.

4.3.2 Aggregating SIFT Key-Points into Feature Vectors

Comparing and classifying the SIFT key-points on a mobile phone might be a time-consuming process as it potentially involves performing floating-point calculations on thousands of key-point pairs belonging to the training sample set and the images to be recognized. This might make the operation slow to the point of being infeasible, since the input data from the phone's camera will arrive at a faster speed than it can be processed. However, achieving high classification accuracy is paramount and it should not be sacrificed for faster performance. This section outlines various

methods and heuristics that were employed in order to try and improve classification performance.

The Bag of Words Approach

One way of enhancing performance during classification is to drastically reduce the number of the SIFT key-points of the training set. In this manner, the number of comparisons between the training key-points and the testing ones will be much fewer. To achieve this, we employed a procedure which would select the most representative of the key-points from each denomination and then transform or *encode* all the training and testing key-points based on their relationship to these representatives. This encoding would produce a much smaller set of encoded feature vectors for each class. This whole methodology is called the *Bag of Words Approach*, and the resultant set of representative key-points is called a dictionary. The methods we tested when creating the dictionary are outlined below, followed by two procedures we tested for encoding all the key-points using the dictionary.

Using a Random Dictionary

The dictionary is created by picking the set of representative key-points randomly. After providing the number of entries that the dictionary should contain, key-points are selected randomly in a uniform manner from all classes from the training image set.

Using K-Means to Build the Dictionary

The K-Means clustering algorithm is used to create a dictionary. The algorithm clusters the key-points into groups and finds centroids which minimize the intra-group distances of all the group's key-points to its centroid. In more detail, a number of representative key-points equal to the length of the dictionary are first picked randomly as above. We call these selected key-points the centroids. Then, all key-points compute their Euclidian distance to each centroid and cluster around the centroid which is closest. Each cluster re-computes its centroid by finding the mean key-point in the cluster and the process repeats itself until there is no change in the centroids. The resulting centroids make up the dictionary.

Key-Point Encoding

This section details how the original SIFT key-points for each training and each testing image are aggregated into a smaller set of feature vectors.

- Given a list of representative key-points (the dictionary) we take each key-point from our training and testing images and we either:

    1. *Triangle Encoding:* Use the Triangle encoding method which finds the Euclidian distance from all the key-points in the dictionary to the key-point we are encoding and returns a vector of the distances which are less than the mean distance, whilst setting the remaining distances to 0, or,
    2. *Nearest Neighbor entry:* We transform each key-point into a vector with 1s for each dictionary entry which has this key-point as its nearest neighbor when compared with the remaining dictionary entries.

- We average over a number of the above vectors for each training or testing sample so that we can return fewer encoded feature vectors than key-points.

4.3.3 Classifying Banknotes

This section details our attempts of achieving high classification accuracy.

Nearest Neighbor

The simplest approach for determining the class of the SIFT key-points or the encoded feature vectors of the image to be recognized (testing image) is to employ an approach whereby each encoded feature vector is assigned the class of the closest feature vector in the training set. Firstly, for all the feature vectors of the testing image, the Euclidian distance, the angle or the *Histogram Similarity* is computed to all the feature vectors in the training set. Subsequently, for each testing feature vector we find the closest training feature vector and note its class. We also take the distance to the nearest neighbor and invert it in order to create a similarity measure. We keep a total of all the similarity measures for each class. In order to remove any possible skewing effects

that may be created if training classes do not contain the same number of images, we divide each similarity total with the total number of training feature vectors for that class. For each testing feature vector we assign the class with the highest similarity total as its denomination label. A normalized sum of all the similarity measures from all the testing feature vectors which have been classified to a specific class is then used as the distance measure of the testing image to that class.

The *Histogram Similarity* is a similarity measure between two feature vectors computed as follows:

- The two vectors are compared element-by-element and from each pair the minimum is kept.
- The sum of these minimums gives the Histogram Similarity.

Nearest to Second Nearest Neighbor Ratio

To improve classification accuracy of a testing feature vector, we observe that we would be more confident to accept the class label of the nearest neighbor in the training feature vectors set if that nearest neighbor happened to be much closer than any other training feature vector. Otherwise, if several of the training feature vectors are within a small radius from our testing feature vector, then the class label of the nearest neighbor cannot be trusted, as any one of several training feature vectors might have happened to be the closest simply by chance. For this reason, a classification result for a specific testing feature vector is only accepted if the ratio between the distance of the nearest and the second nearest neighbor is below a specific threshold. This threshold has been determined empirically to be 0.85.

Support Vector Machines (SVMs)

Instead of using nearest neighbor to assign class labels to the encoded feature vectors, we could use a more complex but a mathematically more proven methodology. In its simplest form, a Support Vector Machine (SVM) tries to compute the best hyperplane which would separate as accurately as possible the samples of two given classes. In our case, we compute all class pairs and we train one SVM per pair of classes. For each pair of classes, we take the encoded feature vectors created above and we train a specific SVM for that class pair which would be able to

separate them. Then, when we have computed the encoded feature vectors for our testing images, each SVM makes a prediction concerning the class to which each encoded feature vector belongs. The class which has been predicted the most times is the winner.

Breaking the Image into Smaller Patches

To improve classification accuracy another approach was tried whereby all training and testing images are split up into non-overlapping patches of 13-by-13 pixels. These patches are each reduced into a feature vector. The patches from the training images, therefore, make up the training feature set and similarly for the testing images. Then, both nearest neighbor and Kernel Regression were employed in order to classify the testing images. Unfortunately, the accuracy was extremely poor so as to discourage us to further investigate this approach.

4.3.4 Determining if the Object is a Banknote

When instructed by a visually impaired user to recognize a banknote, our system takes snapshots continuously from the phone's camera which are pre-processed 4.3.1 and are fed into SIFT for key-point extraction. The extracted key-points from each captured image are then aggregated 4.3.2 into feature vectors and then compared with the feature vectors of the training samples in order to be classified 4.3.3 according to denomination. The more feature vectors that the system classifies as belonging to a specific denomination, the higher the confidence that the object currently being photographed is a banknote of that specific denomination. After a sufficiently high confidence value has been attained, the system stops taking snapshots and announces, using the phone's built-in synthetic speech, the denomination of the recognized banknote. On the other hand, if the object being captured is not a banknote, the system's classification confidence will not reach the required built-in threshold. The system will continue taking snapshots and nothing will be announced until a banknote is put before the camera.

The classification confidence measure should indicate how similar the image to be recognized is to a certain currency denomination. For example, if the feature vectors of an image are classified so that an equal subset of them belongs to each denomination, then there is no way that we could classify the whole image with certainty and we would want to get a confidence of 0. To

do this, we first find a collection of measures each one indicating the distance of the captured image to each class. This can simply be the ratio of the image's feature vectors which have been classified as belonging to each particular denomination. Then we compute 1 minus the entropy of the above distance measures, which gives as the confidence.

4.4 Evaluation

This section details our evaluation methodology, including how we collected training and testing images of dollar bills and how each of the classification methods described above performed.

4.4.1 Data Collection

Training data was collected by taking clear and complete pictures of bills through the phone's camera under a uniform light source and on a white background. The banknotes used for the training set were placed on a white sheet of paper and exposed to an electric lamp which shone from above in an otherwise darkened room. The pictures were taken by the phone's camera held at the same angle and distance for all samples. The images were then post-processed to remove the surrounding white background so as to leave the clear and complete image of the bill on its own. In total, there were 91 training images used. Of them, 21 were of 1 dollar bills, 28 of 5 dollar bills, 22 of 10 dollar bills and 20 of 20 dollar bills.

All 82 testing samples were captured by a totally blind user using the same phone. Naturally, these images are full of occlusions and may be blurred. The user was asked to take pictures, one bill at a time, in any way he deemed desirable. Thus, many of the testing samples contain partial and distorted images of banknotes, in addition to pictures of the users fingers and of the background furniture embedded in them, 4.1. The user was also asked to randomly move about in the room while he was taking the pictures.

More specifically, from the 82 testing images captured, 17 were of 1 dollar bills, 28 of 5 dollar bills, 17 of 10 dollar bills and 20 of 20 dollar bills. The above counts also include pictures of the same banknotes capture from a different angle/distance by the blind user.

Figure 4.1: Incomplete but clear images

Classification method	**Accuracy**	**Speed**
textbfNearest neighbor	71.6%	2.29 secs
Nearest to second nearest neighbor heuristic	93.83%	2.2 secs
Random dictionary	20.99%	3.94 secs
K-Means	20.98%	5.5 secs
SVM	17.28%	2.22 secs

Table 4.1: Accuracy and speed of each key-point classification method

4.4.2 Results for each Classification Approach

In section 4.3.3 we have described various methods of accurately classifying the SIFT key-points computed from each testing image. Optionally, these methods could be employed after aggregating or encoding the set of training SIFT key-points in an effort to speed up our system 4.3.2. The following table 4.1 shows the accuracy of each classification method along with the time taken to classify each testing banknote image. For the first two methods (Nearest Neighbor and Nearest to Second Nearest Neighbor), the SIFT key-points were used without any encoding. For the next two results presented, a dictionary of 500 entries was created using both the Random and the K-Means approaches on which the Nearest to Second Nearest Neighbor classification method was subsequently run. Finally, a dictionary of 50 entries was used with the SVM method. The encoding of the SIFT key-points using the above dictionaries was performed with the Nearest Neighbor entry method.

From the above table 4.1, we can conclude that the two nearest neighbor approaches, when used on the original SIFT key-points, are much more accurate than any of the approaches which use a dictionary. In fact, even though the number of comparisons performed by both the nearest neighbor algorithms between pairs of training and testing SIFT key-points is much larger than the

number of comparisons that are performed by any of the other procedures which use only a smaller dictionary of encoded training feature vectors, the speed of both the nearest neighbor methods is still superior. The reason for this seemingly unintuitive result must be that the actual encoding of each testing image's SIFT key-points before comparing them with the encoded training vectors in the dictionary dominates the execution time of these algorithms. This could suggest that feature vector comparisons is not the bottleneck on resource-constraint devices and that perhaps another, more efficient approach of limiting the actual number of training SIFT key-points used for the nearest neighbor algorithms should be devised. However, even after trying to use methods such as Voronoi Condensation for removing a great number of seemingly redundant training SIFT key-points from our training set, we were unable to replicate the high accuracy of the simple nearest neighbor approaches. Finally, from the results it is obvious that a very simple heuristic, namely the nearest to second nearest ratio, was able to dramatically improve performance in the second of the two nearest neighbor algorithms. Even though the underlining mechanism by which this accuracy increase was realized escapes us, this result indicates that improving the currency recognition algorithm may simply require good taste in the art of heuristic tweaking.

4.5 Future Work

In our everyday cash exchanges, it is unlikely that we trade paper bills one at a time. More often than not, we remove and place back into our wallets whole bundles of banknotes as part of each transaction. One should expect that our software would permit visually impaired individuals to be able to behave in a similar manner. However, as it is currently designed, our currency recognizer can work with only one banknote at a time and can be confused when shown, for example, a handful of multiple bills. We plan to remedy this situation as part of our future work. This work should enhance our image pre-processing algorithm so that it could partition an image into different regions, one for each separate bill fragment and then work on each region separately. Directions should be provided to inform the user the location in the bundle of each banknote recognized.

Our software has attempted to solve the problem of accessibility with dollar bills. However, as already discussed 4.1.1, banknotes of other currencies might have similar accessibility issues.

It would be hard, however, for any software developer to create a mobile phone-based system which would be designed and tested to work with all the diverse currencies around the world. We aim to allow users to be able to train the system to recognize arbitrary bills, such as those of any foreign currency, by themselves. This would involve the software asking the user for some training samples for each denomination from the specific currency. These samples would be provided under a more controlled environment concerning lighting conditions and the banknotes' orientation. The system would guide the user in creating this training environment and would evaluate the quality of the training samples provided accordingly. The system would then process the sample images, remove noise and train itself to recognize the new currency.

4.6 Summary

We have presented the design, implementation and evaluation of a mobile currency recognition system that provides high detection accuracy for visually impaired users. In our limited sample set, our algorithm exhibited good classification accuracy with high confidence for images that were clear and properly taken even if the currency bill was folded, incomplete or had orientation and rotation effects.

Chapter 5

Choosing which Clothes to Wear Confidently: A Tool for Pattern Matching

Being dressed in a socially acceptable combination of clothes is extremely important in a modern society. Wearing clothes that match in color or design with one another is, to some degree, considered common sense. Visually impaired persons, however, have difficulty matching their clothes as they cannot readily identify their color or visual design patterns. To solve this problem, some visually impaired people rely on the help of their family or friends who help them either organize their wardrobes by placing sets of matching clothes in the same pile, or tag each matching set of clothes with a unique tactile marker or Braille label. However, establishing an organizational structure in one's wardrobe is fragile and extremely tedious, as the same procedure has to be repeated after each time a piece of clothing has been worn. For this reason, many blind people prefer to buy only plain clothes which are of similar colors and which feature no salient design patterns. Even though according to [9], blind individuals are primarily interested in how their clothes feel, they also do not want to neglect their appearance. Some blind people in fact associate popular colors with certain meanings, e.g. red with fire [9].

Electronic devices which are able to recognize and provide the color of any object using audio feedback exist on the market [88]. However, even in cases where other means of color identification are available, such as electronic color detectors and the already mentioned tactile markers, blind people lack the sensory experience to know if a color combination matches. Training oneself to memorize which colors match and which do not can certainly be a solution, but it is hard to achieve fully given the vast number of color-combinations. This work [68] does not fully solve the clothes matching problem but makes preliminary progress by attempting to identify whether samples of shirt/tie pairs match. We employ and then evaluating the accuracy of three standard machine learning algorithms: Ridge regression, a standard neural network and a Siamese Neural Network.

5.1 Previous Work

A set of RFID tags were attached to each piece of clothing in [77] for identification purposes. Information about the clothes was also stored in an online database which employed fashion experts to classify them. The RFID tags could be read by a handheld system which would help the visually impaired user find matching clothes by using information in the online database. Similarly, a set of RFID tags were also used in [43] where a system was built to propose matching clothes to its users based on the individual's personal style, the current weather conditions and the individual's daily schedule.

Some research work to determine which sets of colors are visually compatible with one another based on human preferences was undertaken in [61]. The researchers first attempted to find out whether certain theories of human color preferences can be validated using three large online datasets. Then, they created feature models which could predict the visual compatibility of any set of five colors and which could also improve such a set of colors to make it more aesthetically pleasing. Work specifically targeting the visually impaired was described in [94, 81], where a clothes-matching system algorithmically analyzes pairs of images of clothes, both for matching colors and for similar texture patterns. To identify matching colors, a color histogram is created for each image containing only the dominant colors detected on that image. This dominant color set is subsequently used in conjunction with an edge detection algorithm in order to find which

edges on each image are surrounded by different dominant colors, i.e. they form part of a texture pattern. Radon transforms are then used to determine how much to turn each of the two images so that the detected texture patterns have a similar orientation, whilst histogram equalizations are performed to fix changes due to lighting. Wavelet features and Gray co-occurrence matrices are finally employed to compare the detected textures from each image and statistically determine whether the two images match. At the same time, design patterns on clothing can be classified with the algorithm proposed in [91] by combining both structural and statistical features from wavelet subbands using a confidence margin. Clothes can then be characterized as stripe, lattice, special or patternless. Finally, a method for identifying suits in images of people has been proposed in [30] where a set of suitable color and shape features are described for this purpose.

5.2 Methodology

This section describes how we collected our sample images of shirts and ties, in addition to the learning algorithms we used for classifying them.

5.2.1 Sampling

A total of 41 pairs of images of shirts and matching ties were collected from several clothing websites. 74 x 74 pixel patches were extracted from the front of each shirt and center of each tie 5.1. For our sample set, each pair was included together with a label indicating that they match. Also, non-matching pairs were artificially created by pairing each shirt and each tie with itself, creating a total of 82 non-matching pairs 5.3. In total there were 123 samples in our training/testing set. However, other pairings were also tried, such as the all possible pairings. For the results reported here we chose to go with the simpler approach, as our pairs labeled "non-matching" are certainly so, a fact which cannot be reliably claimed for the non-matching pairs of the all pairs set. This is because many ties can match with one shirt, making some of the "non-matching" labels in the all-pairs set invalid 5.2.

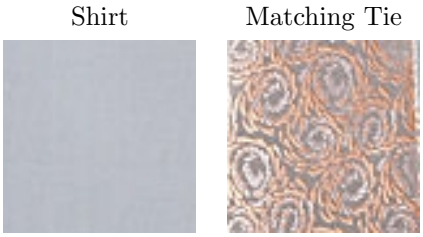


Figure 5.1: A matching pair of shirts and ties

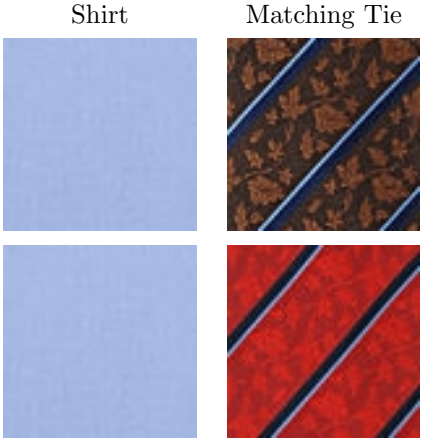


Figure 5.2: The same shirt matches with more than one tie

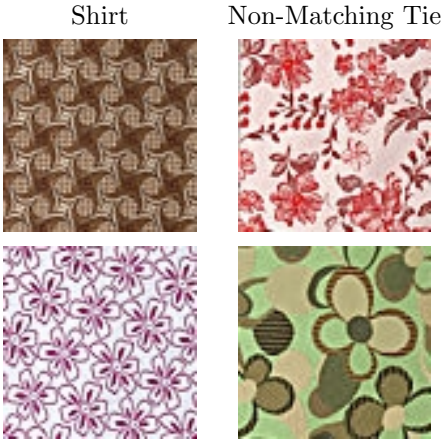


Figure 5.3: Non-matching pairs of shirts and ties

5.2.2 Data Preparation

Each image was used to create a color histogram. The histogram was created by dividing the 3-dimensional color space of red, green and blue into a configurable number of equal bins (we tried experimenting with 8*8*8, 4*4*4 and 2*2*2 bins) and by determining in which bin each pixel falls. This was carried out after the luminance of each image was factored out by normalizing it. Each bin was normalized by dividing with the total number of pixels. Unnormalized histograms were also tried but attained worse performance. The color histograms of each matching pair and non-matching pair, chosen above, were then concatenated into one feature vector and a corresponding label of +1 or 0 was attached.

5.2.3 Learning Algorithms

The following learning approaches were tried in order to classify the computed feature vectors:

- Ridge Regression: This algorithm attempts to calculate the vector of weights which would return for each seen data point its corresponding score. In addition, the penalty term tries to minimize the norm of the weight vector to produce more stable solutions. Although regression is not a classification algorithm, its output can be thresholded to get a classification label. In our case, we set the threshold at 0.5 and so if regression returns a value which is less than 0.5 it receives the 0 (not a match) label and if greater than 0.5 it receives the 1 (a match) label.

- Standard neural network: A network with two hidden layers is trained using either stochastic or batch training, using the Sigmoid as its activation function.

- Siamese Neural Network: The Siamese Neural Network which is described in [27], is implemented as follows:

    1. Two sets of outputs for each layer are stored each one corresponding to one of the two samples in the given training pair.

    2. The loss function is set to the derivative of a hinge loss function, which aims to make the distance between outputs smaller when the pair of images matches but which tries

to make the distance large, but only up to a threshold, when they do not.

3. Uses the same error for the output layer for both images, but reverses the sign of the error for the second image.

5.3 Results

The following table 5.1 shows the regression and the 10-fold cross-validated classification errors for the two of our three approaches (regression and standard) neural network, together with the type one and type two errors, i.e. false-positives over (true-positives + false-positives) for the type one error and false-negatives over (true-negatives + false-negatives) for the type two error.

The Siamese Neural Network was tried with 10 output and 10 and 100 hidden neurons but produced very bad results, (classification error = $\frac{2}{3}$). This is because, as our inputs are structured, the non-matching pairs are made up of two images that are the same in order to give the standard network the most negative samples that it can get. However, it is impossible for a Siamese Neural Network to identify the distance between two identical images, as by definition of this algorithm the distance should be 0. More experimentation is clearly needed by providing pairs which visually do not match but this is left for a future work. In addition, the matchings are not symmetric, meaning that a shirt might match with many ties but not the other way round. A suitable solution perhaps was to add an extra dimension to the input to identify if a sample is a tie or a shirt.

Ten hidden neurons were also found sufficient for the standard neural network in addition to a learning rate value of 0.1, with a binning of 4 for the color histogram as other values did not change the 10-fold cross-validation regression error substantially. The stopping condition for the cross-validation was 0.00001.

The regression error is calculated by taking the Frobenius norm of the difference between the expected and actual outputs for each data point and averaging over all points and over all cross-validation folds.

Algorithm	Regression Error	Classification Error	Type1 Error	Type2 Error
Regression	0.704427	0.175	0.3	0.11253
Neural	0.0955543	0.05	0.125	0.0125

Table 5.1: Performance of learning algorithms

5.4 Summary

In summary, given a sample of 41 pairs of shirts and corresponding matching ties of 74 pixels squared and using a color-histogram of 8 bins, we have shown that with Ridge Regression we can achieve a 10-fold cross-validation classification error of 0.175, with a standard neural network with 10 hidden neurons a 10-fold cross-validation classification error of 0.05 and with a Siamese neural network an accuracy of only 0.33.

From the above results, it appears that the standard neural network exhibits a superior performance over the Ridge Regression algorithm in this particular problem setting. However, more work is needed, especially in finding more samples for other types of clothes, in order to evaluate these algorithms more successfully and develop a more holistic solution to the clothes-matching problem. Symmetric matching pairs should be found in order to deploy the already designed Siamese Neural Network effectively. More importantly, our algorithm should be enhanced to take into consideration other characteristics of the clothes, such as their texture or their design patterns. The above will necessitate a user study to discover how humans actually distinguish between sets of clothes that match and sets that do not.

Conclusion

We have outlined the development of four mobile applications that can assist the visually impaired in their everyday lives. The problems that these applications have tried to solve are essential issues which continue to plague the blind community. The first has attempted to push the envelope on the important issue of unhindered mobility by demonstrating an indoor navigational system. The second has enhanced the accessibility of modern communication devices by proposing several methods of text input on touch screens. The third, by contributing to the solution of the currency recognition problem, has endeavored to remove some of the obstacles encountered by the visually impaired when accessing printed information. Meanwhile, assisting in overcoming one of the most frequent of daily needs has been the goal of the last application for clothes-matching. Our extensive testing has proven the practical usefulness of our applications in daily scenarios.

The main contributions of our navigation system are an algorithm creating a user-trained topological map for navigation instead of using a pre-developed floor map, as well as an algorithm for counting the user's steps. For the mobile Brailler system, our user study has resulted in a number of important findings, chief of which are the fact that visually impaired users would prefer an intuitive but potentially more inaccurate spatial method for entering Braille, instead of a more complex but stationary one, or a slower but more accurate one. Lastly, with both our currency recognizer and our clothes-matching attempts, we have demonstrated that off-the-shelf feature-extraction and machine learning approaches can be combined in a new way to create assistive software in the field of computer vision. Most importantly, we believe that these applications together provide a suite of important mobile accessibility tools to enhance four critical aspects of a day-to-day routine of a visually impaired user: to navigate easily, to type easily, to recognize

currency bills (for payments) and to identify matching clothes.

In addition to a single overarching goal which is to enhance the daily lives of visually impaired individuals, there is another important factor which unifies the above four applications. This is the fact that all four of these applications take advantage of a single device: the mobile phone. As already discussed, this device has attained unparalleled popularity due to the widespread communication needs of our society which it can so efficiently meet. It has also acquired a rich development platform whose growth has been fueled by this popularity. The fact that we have built four separate assistive solutions which run on this widespread platform is not accidental. It was an experiment to determine both the platform's ability to support such demanding applications and a test of the potential acceptance of these applications within the community of the visually impaired. As this work has demonstrated through our user studies, applications which run on smart phones are met with enthusiasm by the visually impaired, due to their portability and social acceptance. This result indicates that when accessibility aids are attached onto mainstream platforms instead of on specialized devices, they can quickly attain a larger and dedicated user-base, finding their way into many more hands which are eager to provide feedback and assist in their further development. This does not in any way mean that specialized devices do not have their uses and cannot offer their own differentiated affordances which could make them attractive in some situations. However, attaching an accessibility aid to a mainstream device, and especially to the mobile phone, is not only expedient from a marketing point of view. It can also open the way to such assistive applications becoming part of the phone's platform, if popularity demands it. Indeed, by building popular momentum behind assistive solutions, they can in turn "infect" popular software, making it more accessible and usable by all. Thus, accessibility would be regarded as a feature of all software, instead of an add-on required only by the few. In fact, adding accessibility features to all software would make it more flexible, enabling it to cater to the needs of all its users, regardless whether they identify themselves as having a disability or not.

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