Sensor-Based Hand Gesture Recognition in Human-Computer Interaction: Sign Language Applications

PhD Upgrade Review

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Contents

Chapter 1

Introduction

1.1 Background

Sign language is one of the earliest documented methods of communication between primitive hominids. Before the development of the highly structured languages we have today, we used hand gestures, facial expressions and body language to express ourselves (Premaratne, Nguyen, and Premaratne 2010). Today, the majority of those using sign language for daily communication are either diagnosed with a disability or have a family member who has been. More recently, partly as a result of better diagnosis of a wide range of Autism Spectrum Disorders, children with non-verbal or non-vocal autism use a form of sign language to communicate (Bonvillian, Nelson, and Rhyne 1981).

As technology development is accelerating, new fields of Assistive Technology have emerged. Such technology is directed towards developing innovations to help people with disabilities live better lives and integrate more easily into their communities. As a result, healthcare technology innovations are receiving a great deal of attention from the medical field and research is being pursued in healthcare innovations relating to assistive technology.

One of the goals of this research project is to help speech-disabled people interact with technology and use it to communicate in public with those who do not understand sign language. My research focuses on exploring new methods to make this technology more accessible and universal by adding translation features and by more easily allowing customisation for different sign language types such as American Sign Language (ASL) and Makaton Sign Language (Charity 2017).

Hand gesture recognition is perhaps the most significant application of human computer interaction (HCI) research that contributes to innovating technology for sign language users. In such investigations, patterns emerging from hand movement and orientation are classified using sign language segmentation (Han, Awad, and Sutherland 2009). This can be done using two approaches:

1. Vision-based systems
2. Data Glove-based systems

A Vision-based system is a gesture recognition system that is based on computer vision. Such systems employ the usage of cameras (either individually or in multi-camera systems (C. Vogler and D. Metaxas 1998)) to detect the motion of the signer's hands and to translate those motions into segmented gestures. Alternatively, a Data Glove-based system, uses a "glove" that is fitted with an array of gyroscopic sensors (that measure rotation), flex sensors (that measure the bending of the fingers) and accelerometers (that measure the forces acting on the hand due to its own acceleration). The data is streamed from these sensors in real-time and processed by a computer or micro-controller (a small processing chip). This processing engine interprets the motions of the hand into sign-language gestures. After the gestures have been interpreted, using either system, the meanings of each can be "looked up" and their spoken translations can be played from a speaker.

Vision based systems often have low accuracy and require complex programming to isolate the hands from the image backgrounds, making them hard to use in non-controlled environment and almost impossible to use for daily communication or as mobile, wearable devices. Some studies have attempted to improve the output of vision-based systems by adding multiple cameras (C. Vogler and D. Metaxas 1998) or using coloured gloves (T. Starner, Weaver, and A. Pentland 1998).

In contrast, data glove based systems have proven to be more reliable in registering and relaying hand gestures. Data gloves use sensors that can more reliably detect finger flexing, hand movement, and orientation (Anetha K 2014). They can also be simpler than vision based systems. However, such systems are still not robust enough. To quote Premaratne, Nguyen, and Premaratne, "Even with advancements in computer vision, glove based sign language recognition offers the widest vocabulary and the best possible recognition accuracy. However, no recent such system has been reported with very high accuracy". This is possibly because researchers currently seem to be more focused on vision based systems.

There are many versions of the Data Glove that translate sign language to text or speech. Most of these gloves rely on a smart device for output and it seems that none have yet moved beyond prototyping. There is almost no published work showing evidence of sign language data gloves being tested by speech-disabled participants for daily communication. This may be due to the low accuracy, complexity and the high cost of the electronic hardware currently required.

Research Questions:

- **RQ1: How can an assistive technology innovation be made to facilitate communication for people with disabilities who use sign language for their daily communication?**
- **RQ2: How can this innovation be made universal and compatible with different libraries of sign language?**
- **RQ3: How can this innovation be made more accessible and more affordable so that it can be more easily available as a commercial product?**

In this research, I explore the possibility of making a robust, stand-alone Data Glove to translate sign language hand gestures to text and speech. The glove would have sensors to monitor the flexing of fingers and to calculate hand orientation in order to more accurately classify complex hand gestures.

Previous research has shown that many systems have failed because of the vast range of sign language vocabulary they had been manually programmed to process (L. Dipietro, A. Sabatini, and P. Dario 2008). I propose programming a limited vocabulary of signs and rely primarily on machine learningdriven software to train the glove for new words.

The plan to limit vocabulary and simplify recognition is a novel attempt to reduce the size and number of components required for the hardware and reduce the complexity of the minimum required software to use the system, in order to make the data glove simpler to run, easier to wear and cheaper to produce.

Machine learning techniques can be used to allow users to train the glove and upload their own sign language dialects. More features will be added, such as translation and wireless smart-phone communication to make the glove more usable in external environments and more easily integrated into daily technology contexts, in the same way as conventional phones or tablets.

1.2 Research Area

- Assistive technology dedicated to facilitating communication for non-verbal disabilities is still in the research phase - although extensive - and none of the existing data gloves translating sign language has moved into structured testing
- Data gloves prototypes which translate sign language uses expensive hardware components which makes them hard to afford for people who need it
- Existing Sign language gloves are very bulky and expensive and not durable or long lasting with no proper testing to document feedback of performance and always need to be paired with a device to operate
- None of the existing sign language data gloves have plans to take the projects further into production and no studies have been made into the readability of the innovation market to be disrupted in this field
- No working prototype of a sign language glove to translate Arabic sign language or Makaton sign language (used by autistic children) to text or speech has ever been made
- There is no universal sign language and different disabilities have their own variation of Sign Language which means any version of a sign lan-

guage translation glove is limited to cater to one form of sign language

1.3 Research Scope

- Use computation innovation to eliminate communication barriers between people with different disabilities
- Give a voice to those who can't speak
- Facilitate communication between people with speech disabilities and the general public
- Make innovation accessible to improve the life of people with disabilities
- Make assistive technology for communication affordable so everyone can use as an extension of their senses
- Design an affordable and durable solution to translate sign language, detach from existing expensive hardware and resort to reducing hardware size and components by designing a flexi-circuit board, enhancing software, and pairing with machine learning
- Design a wireless and stand-alone data glove which operates independently from any device
- Allow users to record their own sign language hand gestures to the glove
- Catering to different disabilities on both ends of communication: Sign Language speakers and listeners/receivers (Mute: use sign language to replace speech, Deaf: people use sign language to speak to them - also use sign language to speak, Blind: can communicate with speech disabled to hear through the speaker)

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1.4 Proposed Research Outcomes

- To design a robust high quality single board computer device with an arm processor which runs Linux system
- The research will be divided in two main parts:
  1. Prototype Design
  2. Usability studies and analysis
- Research Methodologies: Interaction Research employing user-centred design methods and Grounded Theory in a build-measure-learn iteration.
- Explorative studies of physical tangible interaction with domain
- Multiple studies on low cost accessibility tools
- Introduce the prototypes to explore the extent of the research, focusing on hands sensor based interaction with gestures (sensor based data gloves)
- Recruit real participants with speech disability and children with non-verbal autism who use sign language as the main mean of communication to test the prototypes of the sign language glove - integrate their feedback in the loop of prototype design development
- Use smart machine learning to record and recognize hand gestures to allow users to upload their personalized versions of sign language on their gloves
- Design a web application for storing and sharing new hand gestures
- Focus on stand alone - wireless - mobile - affordable - accessible - durable design

Chapter 2

Literature Review

2.1 Sign Language Applications of Hand Gesture Recognition in Human Computer Interaction (HCI) Research

Gesture recognition is a research field of computer science that is explored in a number of fields, including robotics, machine learning and Human Computer Interaction (HCI). Gesture recognition focuses on the computer recognition of expressions or motions by humans including hands, body language and facial expressions. Lately, HCI has gained a lot of research attention utilizing hand gestures (Chen 2003). There are many applications which employ gestures to control output such as media players, remote controllers, robots and virtual objects or environments (Mäntyjärvi et al. 2004) (Ong and Ranganath 2005). The output of sign language is considered to be "one of the single most prominent applications of hand gesture recognition" (Premaratne, Nguyen, and Premaratne 2010).

Sign language recognition is a valuable application of gesture recognition research. Researchers have explored the idea that sign language hand gestures can be used to interact with computer interfaces (Premaratne, Nguyen, and Premaratne 2010). The advancements in sensors, accelerometers and infrared cameras further enhanced the accuracy of recognition modules.

Since the 1990s, there has been lots of research into developing technology for sign language users (T. Starner, Weaver, and A. Pentland 1998). Advancements in hand gesture recognition research has helped improve recognition for sign language assistive technology. Sign language hand gestures can be recognized by processing four patterns: "hand shape also known as hand configuration, hand movement, orientation and classification." (Zhang et al. 2009).

> "Today the focus has shifted again from the mundane use of sign language to the more advanced human machine interaction. This would in effect advance the interactions that disabled people would have with technology as well as make sign languages easily understandable by ordinary users. The technology can also pave way for automatic translation to other languages in other parts of the world making a silent communication revolution for the disability. Yet, the challenges are enormous and the different approaches taken by researchers around the world have shed light on difficulties ahead as well as the progress made so far." (Premaratne, Nguyen, and Premaratne 2010).

In this section I discuss various approaches taken by researchers, over the last two decades, to enhance the accuracy of hand gesture recognition and expand its applications.

I start with an overview of the historical development of hand gesture recognition in HCI research, highlighting the invention of data glove-based control interfaces and how that was eventually combined with computer vision, where gloves used markers and colours for finger tracking rather than sensors, leading up to the glove based systems we know today.

2.2 Overview of Hand Gesture Recognition Research in Human Computer Interaction HCI Since the 1980s

In this section, I collate a non-exhaustive summary of hand gesture recognition prototypes highlighting elements which relates to my research.

Humans have always used hand gestures as a natural means of non-verbal communication. The field of Human Computer Interaction (HCI) incorporates extensive literature on research for recognizing hand gestures through machine learning, for the purpose of replacing keyboard and mouse interaction with electronic devices (Takahashi and Kishino 1992). For the last few decades, hand gesture recognition research has made significant contributions to interactive human-machine interfaces and virtual environments (Takahashi and Kishino 1992).

Some gesture recognition studies focus on static hand postures (Kılıboz and Güdükbay 2015), while others analyse dynamic hand motions (Rigoll, Kosmala, and Eickeler 1997). HCI interpretation of gestures require the posture and movement of hands, arms and sometimes other parts of the body to be measurable by the machine (Pavlovic, Sharma, and Huang 1997).

Since the 1980s there have been a number of studies dedicated to developing gesture-based interaction techniques in the domain of HCI (Rautaray and Agrawal 2015). These studies are mainly classified as glove-based or vision-based (Rautaray and Agrawal 2015) (Pavlovic, Sharma, and Huang 1997).

The first research approach to recognize hand gestures was to measure the bending of finger joints and hand orientation by designing special gloves called "Data Gloves" (Rautaray and Agrawal 2015) (Pavlovic, Sharma, and Huang 1997) (Takahashi and Kishino 1992) (Liang and Ouhyoung 1998). Data Gloves are gloves wired with flex sensors (sensors to measure finger bends and joints angles), accelerometers and gyroscopes which are used to measure hand orientation and direction. Data Gloves have proved to be very reliable in relaying hand gestures position and motion data (Mitra and Acharya 2007). However, the multiple wires which connected the gloves to the computer limited users' mobility. This led to the development of a wireless approach to gesture recognition defined as "vision-based systems" (Rautaray and Agrawal 2015) (Pavlovic, Sharma, and Huang 1997). Vision-based hand gesture recognition systems employed multiple cameras to classify hand gestures but required complex software for image processing to isolate the hand gestures and dealt with finger occlusion (Shen et al. 2012).

Before flex sensors was available, researchers used light tubes (L. Dipietro,

A. Sabatini, and P. Dario 2008), fibreoptic (L. Dipietro, A. Sabatini, and P. Dario 2008) and resistive ink (LaViola 1999) to detect if fingers were flexed or bent.

The earliest documentation of a sensor-based Data Glove was developed in 1983 by Gary Grimes (L. Dipietro, A. Sabatini, and P. Dario 2008) commissioned by “Digital Entry Data Glove”. This glove was wired with multiple sensors. Touch and proximity sensors were attached to determine if two fingers were making contact with each other. Flex sensors were placed over the knuckles to measure fingers bending. And a tilt sensor was positioned at the wrist to detect hand orientation. This glove was programmed to recognize 80 “alphanumeric characters”. Despite the complex circuitry, this glove had low accuracy rates and had heavy wiring. The development of this glove stopped at the proof of concept phase and never made it to commercialisation.

“MIT Data Glove” (Premaratne, Nguyen, and Premaratne 2010) was one of the earliest advanced data gloves of the 1980s. It became a commercial product for the gaming industry and was considered a pioneer in HCI research to replace keyboard input. Registered as acceleGlove (*AcceleGlove* 2016) (*AcceleGlove Dr.Jose* 2017), the glove was wired with an accelerometer to record hand and finger movement in 3D. acceleGlove has applications in video games, sports training, physical rehabilitation and virtual reality. It is costs between \$1000–\$5000[1].

More data gloves started to appear in the industry, designed for motion capture, music applications and animation. I mention below three examples that made headlines: *CyberGlove II & III* (*CyberGlove II* 2017), *5DT Data Glove* (*5th Dimention Technologies* 2017) and *P5 Glove* (*P5 Glove* 2017). These gloves were highly accurate but very expensive and could only be operated by professionals and in a studio setting.

CyberGlove II and CyberGlove III are two generations of data gloves developed by CyberGlove Systems (*CyberGlove II* 2017). They are designed for motion capture for the motion picture, visual effects and animation industries. These gloves are wired with 22 sensors including flex sensors and a

[1]Cost is an important consideration for this research. Making an affordable and accessible glove is highlighted as one of the research goals.

WiFi^{TM}chip to send data wirelessly to a controller computer.

5DT Data Glove was also designed specifically for motion capture for the motion picture and animation industries (*5th Dimention Technologies* 2017). It is wired with an array of sensors and is Bluetooth^{TM}enabled to allow the provision of a wireless data transfer system, running in real time (*5th Dimention Technologies* 2017).

X-IST Data Glove (*X-IST Data Glove* n.d.) is a motion capture glove with touch sensors placed on the fingertips. It was designed to be used for music related applications. It connects to the computer via a USB cable (*X-IST Data Glove* n.d.).

A great example of a data glove which replaced keyboard and mouse input for gaming is the P5 Glove developed by MindFlux (*P5 Glove* 2017). The P5 Glove is wired with bend sensors and remote tracking technologies. It was designed to be used for interactive 3D and virtual environments in gaming and educational websites (*P5 Glove* 2017).

The P5 Glove was developed by MindFlux^{TM}as a way to provide a cheaper alternative to many expensive wired gloves available in the market that can be used for gaming (*P5 Glove* 2017). The P5 incorporates a flex sensor as well as remote camera tracking technologies. It provides users intuitive interaction with 3D virtual environments; such as games, websites and educational software. Data Gloves have come a long way in employing advanced sensor technology resulting in satisfactory hand gesture recognition output. However, they remain heavy in wiring and are still largely extremely expensive to manufacture. Vision based recognition systems proved to be more convenient in terms of hand gestures (Lamberti and Camastra 2012), as they do not constrain the flexibility of hand movements. However, they still retain other issues as described below.

Although my research focusses on sensor-based Data Gloves for hand gesture recognition, I will highlight briefly the history of Vision-based systems, how they works and how they compare to glove-based gesture recognition.

In the early stages of vision based recognition systems, low resolution cameras and limited computer power made it very difficult to isolate gestures. Non-wired coloured gloves were sometimes used to enhance recognition.

With the advancement of video cameras and fast computing, researchers have moved towards developing vision based gesture recognition systems employing real-time vision processing software (Pavlovic, Sharma, and Huang 1997).

The earliest computer vision gesture recognition system emerged in the 1980s (Premaratne, Nguyen, and Premaratne 2010). Camera based recognition had very low accuracy at the time due to low computing power and cameras low resolution. Coloured gloves was then introduced to help the camera in tracking hand gestures (James and Mubarak 1994). This was a glove developed by MIT Media Lab where the finger tips were marked with coloured LED which created different "illumination patterns for different gestures" (Sturman and Zeltzer 1994) which could then be segmented and interpreted by the computer.

Occlusion resulted in very poor performance of the glove, especially since there were many variations in hand gestures when performed by different users.

Vision-based recognition modules used multiple layers of feature extraction software, skeletal tracking, sample matching and 3D positioning (Berci and Szolgay 2007). However, researchers were only able to extract static gestures. Extracting dynamic gestures was still not possible with this approach.

More attempts were made at combining coloured gloves cameras for vision based hand gesture recognition. The earliest of which was reported by Davies et al. (James and Mubarak 1994) who used gloves with coloured finger tips combined with with a grey-scale camera. The system was able to determine seven hand gestures and was mainly designed as a proof of concept as opposed to being a commercialisable product.

Although these approaches represented progress, the problem of occlusion remained. It was later addressed specifically by multiple studies. The earliest being in 1996 by Iwai et al. (Iwai et al. 1996) who introduced the decision tree method to allow the computer to recognize different gestures. The results of this study led to the creation of further research, including the first system to be used for virtual reality applications (R. Y. Wang and Popović 2009)

The late 1990s witnessed a shift in approach for vision based hand gesture recognition systems. Researchers were able to develop hand recognition systems which relied on computer vision but that did not require the use of gloves or markers (Rehg and Kanade 1994). This was due to improvements in camera technology, resulting in enhanced resolution and also more reliable detection and analysis. Researchers added a second and in some instances, a third camera to improve the recognition of hand gestures (Gennery 1992) (Darrell and Pentland 1993). Depth cameras were later introduced and proved to be revolutionary.

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The late 1990s witnessed a shift in approach for vision based hand gesture recognition systems. Researchers were able to develop hand recognition systems which relied on computer vision without gloves or markers (Rehg and Kanade 1994). This was due to improvements in camera technology, resulting in enhanced resolution and also more reliable computing power. Researchers added a second and in some instances, a third camera to improve the recognition of hand gestures (Gennery 1992) (Darrell and Pentland 1993). Depth cameras were later introduced and proved to be revolutionary.

For the first time, real-time gestural extraction was demonstrated in 1995 (Bobick and Wilson 1995) (Utsumi and Ohya 1999) through the use of depth cameras. However, this required a static background to be present behind the subject.

At the turn of the millennium, vision-based hand-gesture recognition systems were finally able to identify a growing number of gestures in real time, but only for static gestures. This encouraged researchers to combine the new multi-layered gesture recognition software with the latest camera technology; in an attempt to decipher dynamic hand gestures using computer vision (T. E. Starner and Benton 1995).

As hardware technologies improved, high resolution cameras became easily available to researchers and at a low cost, compared to the more expensive versions used in previous vision based studies. As a result, researchers "devised new ways to rely on feature extraction from the high quality images available instead of sophisticated multi camera system" (Chen 2003).

A pioneer study in recognizing dynamic hand gestures using computer vision was done by Chen et al. (Chen 2003) in 2003. The system was designed to recognize dynamic hand gestured in real time against a static background. Recognition accuracy levels were above 90% in identifying 20 gestures. The system used complex multilayer software employing hand tracking, feature extraction, Hidden Markov Model (HMM) training and gesture recognition (Chen 2003).

Many studies followed ("A Man Machine Communication System based on the Visual Analysis of Dynamic Gestures" 2005) (P. Premaratne and Q. Nguyen 2007a) (N. D. Binh, Shuichi, and Toshiaki Ejima 2005) (N. Binh and Ejima 2006) (Berci and Szolgay 2007) using different approaches for vision based gesture recognition. Results vary but the primary challenge remains in isolating hand gestures from the background and retaining the mobility of the system.

"The development of the computer vision based gesture recognition will have to go a long way in realizing what has been achieved by glove based systems. No single one prominent strategy in camera setup to feature extraction to classification has been established as the research indicates different trends in myriad of ways. Yet, a powerful application such as sign language stands to challenges the brightest minds to develop the best of approaches in the above areas for a cohesive solution" (Premaratne, Nguyen, and Premaratne 2010).

It is important to note that computer-vision based hand-gesture recognition will never be mobile as it relies on high resolution cameras and powerful computing to be successful. In this sense, comfort and cost can be overlooked and glove-based hand-gesture recognition have a better chance on multiple counts to serve as a communication tool for modern sign language users.

I will now narrow down hand gesture recognition to focus on sign language hand-gesture recognition and how it evolved with both vision based and glove bases systems. I will particularly emphasize American Sign Language as it is what I am basing my recognition schemes on, though they could equally be applied to other forms of sign language. I will also show examples of other forms of sign language.

Sign language hand gesture recognition research builds on the background research summarized above.

2.3 The Development of Sign Language Recognition Systems to Date

A central goal of Human Computer Interaction research is to explore the use of new types of interfaces that use different kinds of inputs, for example human gesture. By the 1980s, systems had "..already been developed to react to limited hand gestures, especially in gaming and in consumer electronics control." (P. Premaratne and Q. Nguyen 2007a).

Since then, hand gesture recognition research has been used to attempt to decipher sign language (Kawai and Tamura 1985a). There are a range of different sign language libraries and types, just like any language and these vary from one region to another.

My research focuses on classifying American Sign Language (ASL) hand gestures using a machine learning software that can then be trained to recognize customized sign language.

I chose American Sign Language because it is widely used by the hearing impaired and deaf communities in the USA, Canada and many English speaking countries (Padden 2011). Recent statistics estimate a range of 500,000 people around the world use ASL including immediate family members of speech disabled individuals (Neidle, Bahan, et al. 1998a).

It is important to identify the fundamental features of ASL to accurately address segmentation and classification research queries. Finger spelling, hand orientation, facial expressions and body language are essential elements to be considered (Costello, 2008). A good example for facial expression is raising the eyebrows to indicate a higher pitch or to ask a question. It is also important to consider that some sign language hand gestures are static, while others are dynamic (Armstrong and Karchmer 2009).

Different research approaches employ different classification methods. However, they all use a combination of the elements identified above.

Just like hand gesture recognition systems, sign language recognition systems are based on either computer vision or data gloves.

2.4 Computer Vision Based Sign Language Recognition Systems

Computer vision based sign language recognition systems are divided into two categories: static gesture recognition and dynamic gesture recognition (Manjula B. Waldron and Kim 1995) systems. Static gesture recognition is designed to classify isolated hand posture whereas dynamic gesture recognition records and processes continuous hand movement. Both static and dynamic hand gesture recognition systems face the challenge of isolating the hand gesture from the background, not to mention incorporating body movement and facial expression for an accurate translation of sign language.

Depth cameras and coloured marker gloves were used to help the computer isolate hand gestures. This proved to be very difficult in non-controlled environments, limiting recognition to labs and research facilities. As a result, computer based recognition systems were never upgraded to become mobile systems. The size and high cost of the equipment also made it difficult to test outside of the lab.

I mention here, in chronological order, previous research that has attempted to enhance sign language hand gesture recognition using computer vision utilizing the same methods highlighted above in hand gesture recognition research background.

The earliest accurate system was reported in 1988 by researchers Kawai and Tamura of Osaka University. Kawai and Tamura published a study featuring their attempt at machine recognition of Japanese sign language in real-time (Shinichi Tamura and Kawasaki 1988a). In this study, Kawai and Tamura used image processing techniques to recognize 20 Japanese hand gestures. They could isolate hand gestures from the background by “comparing a grey scale intensity of two consecutive image frames” (Shinichi Tamura and Kawasaki 1988a).

A decade later, in 1995, MIT researchers Starner and Pentland published research on “dynamic gesture recognition and classification based on coloured gloves and Hidden Makov Model (HMM) classifier” (Starner and Pentland 1995b). They reported a 92% success rate in accurate translation of ASL without explicitly modelling the fingers, rather, by deciphering hand outlines. Recognition models were based on camera tracking of colored gloves. Their system used a limited vocabulary of 40 hand postures (Starner and Pentland 1995b).

In 1997, Grobel and Assan, researchers at Aachen University of Technology in Germany, utilized HHM classifiers for a video based recognition system of Netherlands sign language (K. Grobel and M. Assan 1997). They designed a vision-based system to recognize 262 isolated hand postures. Accuracy level was reported at 94%. They also used coloured gloves but with an improved design to enhance accuracy levels.

By 2000, most vision based recognition systems incorporated both static and dynamic sign language hand gestures. This was referred to as local (hand posture and location) and global (hand movement and path) information (Imagawa et al. 2000).

The first research addressing both local and global gesture information was by Imagawa et al. in Japan (Imagawa et al., 2000). They used a clustering technique to layer multiple images of hands extracted from sign language images. Accuracy was recorded at “...around 94% which was a significant achievement given that they relied on very low resolution images” (Premaratne, Nguyen, and Premaratne 2010).

In 2004, researchers Vogler and Metasas at the University of Pennsylvania also devised both static and dynamic gesture recognition system for ASL but this time relied on HMM and 3D motion analysis” (Christian Vogler and Dimitris Metaxas 2004). Their system was the first to “...break down the signs into their constituent phonemes, modelling simultaneous events in stochastically independent channels” (Christian Vogler and Dimitris Metaxas 2004). They used a vocabulary of 22 signs and three channels to validate their system. Results were satisfactory at 96%.

Another breakthrough in 2004 was the employment of neural networks to classify sign language hand gestures feature extraction.

A pioneering approach using neural networks to recognize sign language hand gestures was attempted by Isaacs and Foo in Florida. Similar to Imagawa et al. (Imagawa et al. 2000), Issac and Foo also used hand images for attempting video-based sign language recognition. However, they utilize a vector to feed a neural network that recognizes the ASL alphabet (Isaacs and Foo 2004). Their system results in 99% accuracy in the context of finger spelling. They plan to expand recognition models by designing "algorithms for ASL feature vector recognition" (Isaacs and Foo 2004).

The above studies suggest that sign language hand gesture segmentation has high accuracy results. More recent research has built on this theory combining it with new emerging computational technologies.

The debut of Kinect had a very strong impact on the sign recognition community. Kinect offered real time tracking in 3D and successful hand gesture isolation. This presented a "short-cut to real time performance and made recognition possible in different environments" (Cooper et al. 2012).

A recent study in 2012, conducted by Cooper et al. at University of Surrey presents a what they call a "sophisticated sign language recognition system based on Kinect" (Cooper et al. 2012).

For sign language recognition, Cooper et al. used a two-stage recognition system based on linguistic sub-units paired with Kinect 3D hand tracking in real time. The collected data was combined using a sign language classifier. A neural network was then employed to encode the variations in sub-units (Cooper et al., 2012). This approach resulted in recognition rates of 99% based on a 20 sign multi-user data set and 81% on a 40 sign test set.

Cooper et al.'s research is a culmination of all previous research in the field of gesture recognition based on computer vision and is the most comprehensive effort to date. It was published in many machine learning journals and HCI conferences.

Sign language recognition based on computer vision gives high accuracy rates when it is used with a limited vocabulary of trained signs. As the number of words increase the accuracy rate declines (Fang, Gao, and Zhao 2003). Results vary greatly between different users due to the variation in hand shapes, speed, position and orientation. Sign language libraries are enormous with some signs being very similar and difficult to distinguish. Computers still struggle with isolation, depth, classification and segmentation. Sophisticated software and multi-stage processing is required to recognize sign language. As a result, it is unlikely that these systems can exist yet as accessible mobile devices or become available universally to sign language users and deaf communities.

It is for these reasons that I opt to exclude vision based recognition systems from my research and emphasize on data glove based sign language recognition systems.

2.5 Data Glove Based Sign Language Recognition Systems

Data glove based systems have proven to be more reliable in registering and relaying hand gestures than vision based systems. Data gloves use sensors that can more reliably detect finger flexing, hand movement and orientation (Anetha K 2014) as well as global and local features. Data glove recognition systems are simpler than vision based systems because they don't have to consider background isolation or hand motion tracking.

There are many versions of the data glove that translate sign language to text or speech. I mention here the earliest prototypes and how they progressed to the versions we know today.

One of the earliest attempts to translate sign language hand gestures to speech was Fels and Hinton's Glove Talk (Fels and Geoffrey E Hinton 1993) in 1992. They used a data glove and a speech synthesizer to translate 66 root words with six different endings and a vocabulary of up to 200 words.

Their data glove is wired with sensors to collect finger bending data and hand orientation over 16 parameters which is measured every $\frac{1}{60}^{th}$ of a second. The data is then sent through a computer which defines the text and sends it to a speech synthesizer to translate it into human-like speech. The computer starts processing when it detected a motion from the glove. A stop in motion gives the computer a message of the end of the gesture and it stops processing. One of the challenges they faced was adjusting the singing speed to tell the system when to start/stop processing. Another challenge was the response delays due to the fact that three different software were being used at the same time and sharing the same memory. Glove Talk resulted in 1% incorrect output and 5% non-identifiable gestures. The system was not tested with different users to observe system adaptation to user variation.

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In 1998, building on Fel's and Hinton (Fels and Geoffrey E Hinton 1993) Glove Talk system, researchers Liang and Ouhyoung (Liang and Ouhyoung 1998) from National Taiwan University were able to interpret Taiwanese sign language in real time using a data glove and HHM. They first solved the end-point detection problem - a major challenge for Glove Talk - by creating a threshold for gesture time variance. They classified recognition models based on four gesture parameters: "posture, position, orientation and motion" (Liang and Ouhyoung 1998). Their prototype system was programmed to recognize a vocabulary of 250 words with an accuracy rate of 80.04% In 2003, building on both Fel's and Hinton (Fels and Geoffrey E Hinton 1993) and Liang and Ouhyoung's (Liang and Ouhyoung 1998) research, Fang et al. (Fang, Gao, and Zhao 2003) attempted to develop an advanced sign language recognition system by improving processing speed for a large vocabulary of sign language based on hierarchical decision trees. They acknowledged that output delays were due to the systems being programmed to recognize more words and so their proposal helped the computer prioritize which clusters to look through first. Fang et al‘s research addressed and solved a major challenge in previous data gloves - how to reduce recognition time without the loss of accuracy. Their testing results show processing speed was 11 times faster than previous systems and was able to process a vast vocabulary of 5113 words.

In 2011, a different approach to sign language recognition systems was proposed by Oz and Leu (Oz and Leu 2011) who used a motion tracker, an artificial neural network and a sensor glove to translate ASL to speech. Three sets of data was collected and aligned for an improved classification of sign language. Finger and hand shape data was collected from the sensory glove. Hand motion data was collected from the motion tracker. Both data were then classified by the artificial neural network. Gestures feature extraction was continuously being performed in real time. The system was trained to recognize 50 ASL with accuracy results of 90%.

2.6 Current Academic Projects and Early Prototypes of Sign Language Data Gloves

Sign language recognition technology is currently being developed by many research teams at universities and digital health labs. Recognition systems are still based on either computer vision or data gloves. However, researchers continue to explore solutions that bring them closer to producing a reliable system which could be integrated into the speech-disabled community and enable them to express themselves more naturally.

In this section I mention some of the most significant academic research projects in this field and highlight the features and limitations of this work. Many of these projects build on the literature mentioned above and show great promise but have not yet moved beyond the research phase to testing or production.

Perhaps one of the earliest academic debuts of a working sign language data glove was AcceleGlove, developed by researcher Jose Hernandez-Rebollar at George Washington University in 2003 (*AcceleGlove* 2016). AcceleGlove was presented as an experimental device that translated the hand gestures and body language of American Sign Language (ASL) into spoken words. AcceleGlove was perceived as a wearable computer with very small electric circuits which was considered revolutionary at the time. AcceleGlove is a right-hand glove with two small armbands, for the wrist and the upper arm. The glove is wired with sensors and a micro-controller attached to the wrist, mapping the placement and movement of the arm and fingers. The collected data from the sensors is processed by the computer and converted into speech spoken out through a speaker or text displayed on a computer screen. This single glove can produce up to 200 words which could be signed using only one hand and a few expressions. As for accuracy, Jose Hernandez-Rebollar stated that "the device usually is accurate, though the precision declines with complicated movements; for example, words that start with the same hand movement or orientation" (*AcceleGlove* 2016). This was one of the most powerful data gloves in terms of output to be published in 2003. However, the processing happens on the computer itself as well as the text display, so AcceleGlove could not operate as a mobile device (*AcceleGlove* 2016).

In 2012, a data glove was designed and programmed by two Ukrainian students to translate sign language into speech. The glove was called Enable Talk and took part in a competition organized by Microsoft in which it got the first prize3. Enable Talk is fitted with "flex sensors, touch sensors, gyroscopes and accelerometers, as well as some solar cells to increase battery life" (*EnableTalk* 2017). The glove has a system that can translate sign language into text and then into spoken words using a text-to-speech engine. The whole system then connects to a smartphone over Bluetooth^{TM}(*EnableTalk* 2017). A major drawback is that the Enable Talk system mostly uses Microsoft technology and is not compatible with any other platform.

The team has built a number of prototypes and claim to have tested them with sign language-users in the Ukraine, although no documentation of usability studies have been shared or published. Enable Talk would have been highly competitive if introduced into the market because it was set to cost under $100 and also promised to come equipped with a software the enables the users to teach the system new gestures and eventually build a library of custom gestures (*EnableTalk* 2017). However, no further research has been done on this project since 2012 and it did not move into production (*EnableTalk* 2017).

In 2013, inspired by Jeremy Blum‘s innovation, the Sudo Glove (Blum 2012), which is a sensor data glove for non sign language applications, Roman Rozak set out to create a device that could utilise the same technology (flex sensors, accelerometer and microcontroller) while accomplishing a completely different task: translating sign language into text and speech. Roman Kozak, a high school student at the time, is probably the youngest programmer who designed a glove-based sign language translator. He was also the first to program an Arduino to read analog data from flex sensors and outputs them as letters matching the sensor data with a serious of if-statements. The accuracy levels were outstanding. However, it was still limited to letters, specifically, one letter at a time. Letters were not aligned to form sentences. Rozak stated that “distinguishing between similar sign language gestures was very challenging” (Rozak 2017). Processing and display of letters happened on a computer screen or a smart device tablet sent wirelessly via bluetooth. Kozak has now stopped working on this glove and instead moved on to create a similar innovation with different technology (Rozak 2017).

In 2014, Gesture Glove (*Cornell University Glove* n.d.) was another project that generated significant press attention. It was designed by two groups of students at Cornell University who have developed a different version of a glove which translated sign language to speech. Designed and built to be worn on the right hand, this glove used a machine learning algorithm to translate sign language into words (*Cornell University Glove* n.d.). The glove hardware is very similar to previous gloves, including most data gloves (Prashan Premaratne, Ajaz, and Malin Premaratne 2013a). It consisted of five flex sensors, a gyroscope and a microcontroller. The incoming data from the sensors are sent serially to a computer to be analysed in conjunction with a Python script. By collecting a moderate amount of this data for each letter or word and feeding it into a machine learning algorithm, it can train over this dataset and learn to associate a given hand gesture with its corresponding sign (*Cornell University Glove* n.d.). It is interesting that the glove continuously learns from the user. However, there are important lack of accessibility features to discuss about this glove. First, much of the computation happens on the computer and not the glove itself, which makes the glove heavily reliant on a computer to operate. Secondly, from an accuracy point of view, in some cases, the change in the resistance from the flex sensor will be negligible and the algorithm may be unable to discern the difference between these signs. Thirdly, this glove is only programmed to recognize and output letters, which is not necessarily practical for sign language users. The hardware is bulky at this early prototype state, making it difficult to wear.

Also in 2014, Anetha K, assistiant professor at the Institute of Technology, Coimbatore in India, developed a sign language recognition data glove called Hand Talk (Anetha K, 2014). Hand Talk uses artificial neural network (ANN) to translate the American Sign Language (ASL) alphabets into text and sound. The glove circuit consisted of a controller unit, text to speech conversion module and a LCD display. The glove itself uses wired with flex sensors, a 3-axis accelerometer and sEMG sensors to capture gestures (Anetha K 2014). Just like previous data gloves discussed above (*AcceleGlove* 2016) (*EnableTalk* 2017) (Rozak 2017) (*Cornell University Glove* n.d.), the flex sensor produces the change in resistance value depending on the degree of bend in each finger. The corresponding hand movement and orientation is reported by the tri-axial accelerometer. A novel aspect of this technology is its use of sEMG sensors, which are used to measure the muscle activity of the hand while performing gestures in terms of electrical signals. The recognized gesture are then converted and displayed as corresponding text and speech using a text to speech conversion module (Anetha K 2014). This glove builds on all previously discussed glove prototypes. Testing for Hand Talk was published based on its ASL alphabet output only, which again makes it not necessarily practical for sign language users. Hand Talk hardware is not wearable. Output relied on a computer to display letters and to produce sound (Anetha K 2014).

The latest and most recent sign language translation data glove prototype was developed by researchers at Mexico's National Polytechnic Institute (IPN). This prototype, created by Miguel Felix Mata and Helena Luna Garcia, senses hand movements of the user and identifies them with the 26 letters of the English alphabet (*Mexico's National Polytechnic Institute* 2017).

Once the message reaches the device, it plays a voice. Listeners can then understand what their differently-abled companion or acquaintance is trying to say. Presently, the glove can only read letters of the ASL alphabet, but the researchers indicate that Mexican sign language support is a target feature. Smart textiles with conductive features have been used to detect if the fingers are open or closed. A combination of nylon and polyester was used to support the embedded hardware and give the glove better manoeuvrability. "Words and phrases are transmitted by Bluetooth$^{\mathrm{TM}}$to a mobile device with a preloaded application that displays and reads the signs," (*Mexico's National Polytechnic Institute* 2017) Luna said. This by far is the only sign language data glove that has paid attention to glove materials, appearance and durability. This is also the only glove which designed an application for smart devices to pair with the glove for output. The application is available on the Android platform as Glove Translator but needs the glove to work. The main drawbacks of this prototype are the size of the glove and the output mode. It depends on the app for output and cannot operate as a stand-alone glove. This glove prototype is awaiting patent and manufacturing (*Mexico's National Polytechnic Institute* 2017).

In summary, all data gloves described above are single gloves, specifically right hand gloves, they use ASL based libraries to process alphabet letters, they all use an external device for output and some of them are extremely bulky and non-wearable.

My goal is to enhance performance and increase accuracy in comparison with existing data gloves, by making a stand-alone data glove which is accessible, universal and wearable.

Rather than output single letters, to aim for the glove to process words to form sentences and program a software which can help structure grammatically accurate sentences derived from action words. Although sign language users only sign action words and don't form full sentences when they sign, the person receiving the speech is costumed to communicating in full sentences.

Instead of relying on a smart device or a computer, to design a wireless and stand-alone data glove with all required hardware for output is embedded in the design of the glove and powered with a battery. The challenge for this approach is to reduce hardware to make it wearable. Consider to pair one right hand glove with a left hand glove and integrate the signals from both gloves to form one more accurate output In order to make this glove universal, pair it with a translation API to output the signs in different languages even though the sign language used is American.

Considering the vast variations in sign language libraries, to equip with machine learning software to allow each user to train the glove using customized hand gestures. This is mostly useful for Autism users of the Makaton sign language library (Charity 2017).

To design a mobile app to sync with the glove for training new gestures and building a customized library. The app could be used to set the speech language or connect to the internet for future upgrades.

To make this glove accessible it must be affordable by trying to reduce hardware and replace it with software when possible and also integrating all parts onto one circuit board.

To make this glove wearable, smart textiles must be utilized and a customized glove design pattern to house all hardware in correspondence with hand and arm ergonomics. Fabric used should be water resistant, machine washable, fire resistant and employ safety measures to insulate the electrical circuit from contact with skin.

Explore the possibility to create a two-way communication scheme where this glove enables both participants in a conversation to understand each other. This could be done by adding a microphone and a speech to text for the reverse side of the conversation.

Chapter 3

Methodology

3.1 Research Methods

Human-problem oriented inventions (Cox and Cairns 2008) , similar to my proposed design of the data glove, have conventionally employed user-centred design research methods (Bevan and Curson 1999). Rather than starting with an idea for a system based on what technology can do, and then trying to determine whether people will be able and willing to use it, instead I will start with people's needs and ability; and find a technology that they will be able to use to fulfil a need. This strategy is confirmed in multiple research resources in HCI (Dix et al. 2004) and is referred to as 'Interaction Design'.

The main steps in such a strategy are the following:

1. Identify a problem that requires a solution, which then becomes the research goal. This can be confirmed through surveys, interviews and observation.

2. Find the source of the problem. What is causing the difficulty?

3. Invent a solution to help people with their difficulty. This can be done through multiple rounds of testing and developing to prove that the proposed solution is valid. Interaction design research will be used in this phase to develop and test iterations of the designed system, in a build-measure-learn loop.

4. Create a system which incorporates findings and make it available to the people who struggled with the previously identified problem. If the function people wanted to perform but couldn't do well is made more available, chances are it will be successful, considering of course it is affordable, which is a major consideration in this research.

For the theoretical part of my research, Grounded theory will be employed, where theory emerges from the collected data which will be gained through multiple rounds of data collection. Interaction design method will then be applied to use the collected data to prove the theory through a series of usability studies which will mainly constitute of demonstration case studies followed by longitudinal & In-depth case studies. This will be discussed in detail in the evaluation chapter. I propose combining Grounded Theory with Interaction Design Research, to structure the iterative design phase of Grounded Theory. I chose Interaction Research because it is more of a holistic approach to problem-solving, rather than a single method for collecting and analysing data (O'Brien, Rory (Faculty of Information Studies 2001). In conjunction with this, user-centred design usability testing will then be used to validate the proposed solution for the identified problem.

3.1.1 Grounded Theory

Grounded Theory started as the analysis of qualitative research data. However, it was later identified as "a method of qualitative research that aims to produce new theories that are grounded in the qualitative data gathered during the research" (Glaser and A. Strauss 1967). Researchers Strauss and Corbin (Strauss and Corbin 1990) used the term "Grounded Theory" to refer to a theory building approach based on an analysis technique they formulated of collected data that can incorporate both qualitative data sets such as interviews, focus groups, observations and ethnographic studies and quantitative data sets such as questionnaires, logs and experimental data. "The research findings constitute a theoretical formulation of the reality under investigation, rather than consisting of a set of numbers, or a group of loosely related themes" (Strauss and Corbin 1990).

Grounded theory is different from other research methods in that it does not require a prior hypothesis before conducting research (Glaser and A.

Strauss 1967). Researchers may approach the research with an identified goal without knowing what they expect to find (Adams, Sasse, and Lunt 1997). “The process of doing the research formulates the theory and therefore produces potential hypotheses for further study” (Adams, Sasse, and Lunt 1997). A side-effect of this is that research data previously collected on the same phenomena can be used for further research.

In Grounded Theory, the theory is developed once there is available data to analyse and not once the data collection phase is concluded. A good example is the first interview, although one interview is not sufficient to base a theory on, it is however a good indication of validating and expanding the theory and leads to a tentative theory (Cox and Cairns 2008). In subsequent interviews, the researcher would design the questions with the intention of testing the limits of the theory. The second interview analysis would either confirm or reject the theory. It may even produce a new theory and so on. “Thus, the method proceeds through cycles of data gathering, analysis and theorizing” (Cox and Cairns 2008). As a result, interview questions progress from the initial interview and are generated based on the results of each cycle of interviews. Questions can be very different later in the study than the very first interview. This approach is applied to different data collection methods throughout the study where the reliability of the method is tested through “systematic repetition of observations in quantitative research” (Strauss and Corbin 1990). Strauss and Corbin (Anselm Strauss and Juliet Corbin 2008) suggest that grounded theory is especially useful for complex subjects or phenomena where little is yet known. This is a major reason why I have chosen it as the main research method for conducting this research. “The methodology’s flexibility can cope with complex data and its continual cross-referencing allows uncovering previously unknown issues” (Anselm Strauss and Juliet Corbin 2008) and grounding of the theory specifically to validate the proposed solution for the identified. Emphasis is placed on theoretical sampling and contextual considerations so that later transferability of finding can be increased. This is useful for new emerging fields of research relevant to innovation and assistive technology. The collected data is analysed in a standard grounded theory format. It is then broken down, conceptualized and put back together in new ways. To enable this to occur in a structured manner, Strauss and Corbin (Anselm Strauss and Juliet Corbin 2008) have devised three major bonding stages – “open, axial and selective" (Anselm Strauss and Juliet Corbin 2008) - in the analysis procedure. The lines between these forms of coding are artificial, as is the division between data collection and analysis. This is an analytic distinction, but in practice, all of these elements of grounded theory analysis intersect as the interpretation proceeds.

Coding categories in my research as identified in the research question are:

- **Assistive:** Effective in facilitating daily communication between sign language users and the public. This specifically measures the performance of the glove, its durability and comfort and mobility.
- **Universal:** Can be used by adults (all genders), children, output different languages, compatible with any platform, translate different libraries of sign language including customized gestures.
- **Accessible:** Can be made available to people who need it, not requiring any external hardware or device, stand alone, wireless.
- **Affordable:** Cost effective – reasonably priced.

The reason I chose to pair grounded theory with interaction design research as my proposed research methodology is because both grounded theory and interaction design research methods employ an "interplay between data collection and data analysis, which results in the concepts and theory truly emerging from the data" (Lazar, Feng, and Hochheiser 2010). In this approach, detailed and through coding is conducted from the multiple rounds of data collection. Results depends on researchers listening to the data. As in most research in the HCI field, both text-based information and multimedia-based information will be collected from the participants (Lazar, Feng, and Hochheiser 2010). However, since I will be designing new technology and studying speech-based interaction, I will also need to evaluate a number of issues relating to the recognition rate, which requires comparison between the recorded data and the system output. This leads me to the description of kinds of methodology that bear on the invention of new computer-based methods (Rogers, Sharp, and Preece 2011) and to be combined with the coding criteria for grounded theory, specifically to evaluate system performance:

Failure Analysis: is to find out specifically where things go wrong. Individual Difference Analysis: This is to identify that certain kinds of users, ones with certain background characteristics or abilities, affect the results of testing the system in different ways. This is directly relevant to my proposed universal design of a sign language data glove to be used by all ages, genders, languages and abilities. Time Profiling: Time profiling is used to measure and analysing how much time Is spent on isolated tasks within the system. Time profiling is important in identifying problems in the system and potential areas for improvement (Cox and Cairns 2008).

3.1.2 Interaction Design Research: build - measure - learn

Referring to multiple resources on research methods in HCI (Cox and Cairns 2008) (Dix et al. 2004) (Lazar, Feng, and Hochheiser 2010) (J. Zimmerman, Forlizzi, and Evenson 2007), I have identified the practice portion of my PhD proposal as interaction design. The start and focus of any interaction design is the intended user or users (Dix et al. 2004). The user in my case is speech disabled individuals who use sign language for their daily communication. My research, design and evaluation will be based on their needs. Consequently, testing rounds will employ user-centred design research methods.

In principle, interaction design research is "learning by doing": researchers identify a problem, design a solution, test and evaluate their proposal, and if not satisfied, try again using the feedback they gained from the research cycle. While this is the essence of the approach, there are other key attributes of interaction design research that differentiate it from other problem-solving research methods. One being its emphasis is on scientific study. In interaction design research, the problem is studied systematically, and intervention is informed by theoretical considerations, which in my case will be the outcome of grounded theory research. In Interaction design research, data is presented on an ongoing basis. All the while, the methodological tools are being refined to suit the demands of the research (O'Brien, Rory (Faculty of Information Studies 2001). Another reason that I chose Interaction design research, is because it is a user-cantered research methodology. Interaction design research focuses on turning the people involved in the studies and

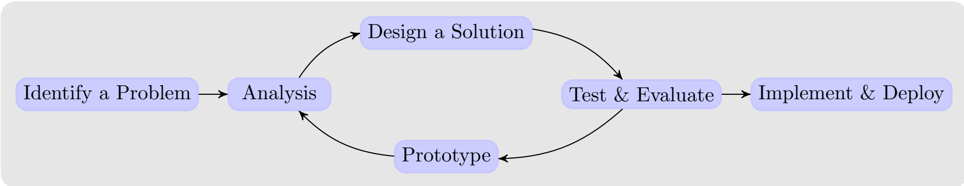


Figure 3.1: Interaction Design Process; based on Figure 4.1 of Dix et al., 2004

testing into researchers, too. "People learn best, and more willingly apply what they have learned, when they do it themselves. It also has a social dimension - the research takes place in real-world situations, and aims to solve real problems" (O'Brien, Rory (Faculty of Information Studies 2001). This is the exact setting for my research studies, where real participants will test and use the data glove, sometimes over a long period of time and mostly in their own environments. The interaction design process (Dix et al. 2004) of the research will be divided into four main phases plus an iteration loop (feeds evaluations back into the deign), focused on the design of interaction, illustrated in Figure 3.1.

Requirements: The first stage is establishing what exactly is needed. As a pioneering study in this field it is necessary to find out what is currently happening. For example, how do speech disabled individuals currently interact in public using sign language? How does the process of communication work? A number of techniques have been documented to be used for this in HCI (Dix et al. 2004) (J. Zimmerman, Forlizzi, and Evenson 2007) like interviews, video documentation and direct observation.

Analysis: Observation and interview are analysed to highlight how people carry out various tasks in relation to the problem identified. The results are classified in a format to outline key issues resulting in task models. Task analysis methods are then developed and applied to formulate a proposal for a design solution.

Design: Design is at the core of the interaction design process. This phase starts with the data gathered from previous steps and moves from what we need to design, to how we should design. Design loops are then attempted based on user testing and feedback, in compliance with user-centred design principles.

Iteration and prototyping: Evaluation of prototypes will be based on usability testing feedback. Observations will be made in terms of performance and improvement areas. Most user interface designs involve some form of prototyping, producing early versions of systems to try out with real users (Bevan and Curson 1999). This is my approach for the proposed data glove design. Prototyping iteration will be discussed in more detail in evaluation methods.

Implementation and deployment: Finally, when the design gives indications that is successful based on user feedback from testing rounds, the plan is to create it and deploy it. This will involve finalising writing code, concluding hardware design, writing documentation and manuals - everything that goes into a real system that can be given to others in preparation for production.

3.2 Evaluation Methods

Evaluation methods will be divided into two overlapping sets (Fallman and Waterworth 2005):

1. Full-scale evaluation studies
2. Formative evaluation and iterative testing

3.2.1 Full-Scale Evaluation Studies

HCI studies have used full scale evaluation to compare the performance of different systems (Wania, Atwood, and McCain 2006). Full scale evaluations are also known to have been used to examine specific features of existing systems for the purpose of further development. In full scale evaluation studies “A group of representative subjects are recruited to learn and use each of the systems and compare them on a pertinent set of performance measures” (Cox and Cairns 2008).

For my proposed data glove prototypes, I will conduct a series of in-depth longitudinal case studies with two groups of users: adults with speech disabilities and children with non-verbal autism. The aim of the studies is to know what will happen to real users over the period of time they will actually use my proposed design of the data glove. These studies will only be feasible by doing direct experiments with real users participating on a full time basis for six months in each comparison group. There are several points to consider for the testing rounds:

- Due to the nature of the participants' disabilities, it is not feasible to conduct studies in a group setting or with big numbers of participants.
- One-on-one time will be needed with study participants to train them on how to use the new technology, keeping in mind that disabilities will vary between users.
- It is common for testing with participants who have disabilities to gain feedback through a care giver, a therapist or a family member (Lazar, Feng, and Hochheiser 2010)

Evaluation criteria will be classified under two main categories: Performance Metrics: Isolating performance features and setting them as evaluation criteria is key to identifying why a system works better than another. One proposal (Roberts and Moran 1983) is to use a set of "benchmark" tests that are chosen to represent the important functions performed with a system.

Usability issues: In users' feedback I will be keen to observe and discover possible trouble-spots in the use of the prototypes, so that solutions can be proposed in the next cycle of prototype design (Klasnja, Consolvo, and Pratt 2011). To be valuable, evaluations of this kind must look at the details of use (time, errors, user reactions) for isolated functions rather than overall performance. Lessons learned from such studies provide important foundation for the development of future systems designs (Cox and Cairns 2008).

3.2.2 Formative Evaluation and Iterative Testing

Cost is a fundamental factor in this research. Therefore, it is important to justify why I intend to conduct multiple rounds of prototype building and testing. Designing multiple prototypes each performing an isolated task and testing this particular feature is more effective than prototyping a fully executed system and testing multiple features at once. "The best strategy for good design is to try various options (suggested, of course, by experience with previous similar systems, guidelines, and available principles), test them, and be guided by the failures, successes and comments garnered in watching their use, redesign trying new options, and iterate. This is called formative evaluation or developmental evaluation. The idea is simple enough. The barriers to its more frequent use are largely lack of will (organizational resistance), lack of time, or lack of ingenuity" (Dix et al. 2004).

It is documented in previous HCI research (Cox and Cairns 2008) (Lazar, Feng, and Hochheiser 2010) that formative testing can be both extremely effective and quite economical. Although a single test is not sufficient, multiple iterations of the whole system are not required to evaluate it. "There are many reports in the literature, of dramatic improvements in usability in cases where two or three iterations were made on each important interface design problem, each requiring about a dozen hours of human testing and an equivalent amount of reprogramming" (Georges and Romme 2004).

HCI researchers (Cox and Cairns 2008) (Lazar, Feng, and Hochheiser 2010) have strongly recommended that user testing begin as early in the development cycle as possible, so that improvements can be made before design processes and coding become complex. For this to become feasible, it is advised to keep the system development flexible and easily modified to be able to conduct continuous user-testing. This is known as "rapid prototyping, and consists of first developing a system specifically designed to be easily modifiable" (Wania, Atwood, and McCain 2006). This is done through segmenting performance and postponing the launch of the full system to a later stage in the study (Dix et al. 2004) (Georges and Romme 2004).

An exemplary case study and rational account of the iterative testing and rapid prototyping approach is given in an article by Good et al. (Cox and

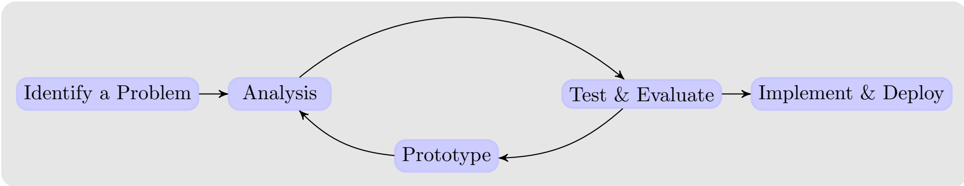


Figure 3.2: Iterative Prototyping; based on Figure 4.2 of Dix et al., 2004

Cairns 2008) in which they describe the process as “User derived interface design.”

In this way, a series of prototypes of the data glove will be designed and a chapter will be dedicated to prototyping: design and programming, following the same structure illustrated in figure 2. First prototype will be a proof of concept, to prove that the system works with minimal hardware and software. Testing will be conducted and feedback will be fed back into the design loop of the next prototype. The consequent prototypes’ features will be upgraded gradually based on usability testing, always considering the four main elements of this research: affordable, accessible, universal and most importantly effective in facilitating daily communication between speech disabled individuals and the public.

As an example, in designing an interface for a prototype voice store and forward system, a first attempt-by an expert human factors team at a set of user procedures produced around 50% unrecoverable errors in attempts to use the service. After four weeks of testing and three revisions in the protocol, field tests found the procedure to result in less than one error for every hundred uses[1]. The voice message system demonstrated by IBM at the 1984 Olympics in Los Angeles[2] was developed by a team of programmers and behavioural scientists who continuously tried new versions of the system and its protocol and made revisions for several months. Despite what would ordinarily be considered a rather small-scale development effort, usability in the initial full-scale trial was extraordinarily good. The development of the much acclaimed user interface for the Apple Lisa computer (including design lessons later incorporated into the MacIntosh) was accomplished by almost continuous formative testing during system and interface development. In

[1] Riley, cited (Cox and Cairns 2008)
[2] Gould and Boise, cited (Cox and Cairns 2008)

this case the testing was done by the manager of the interface programming group himself[3]. The tests were relatively informal. Tesler selected a particular issue, for example where to put an "exit" icon on the screen, for semi-formal evaluation, (i.e. for some subjects it was in one place and for others in another), for each small experiment. Then he would have a handful of subjects try each of the two options. Most of the gain was not, however, from the comparison of the options but merely from observing the difficulties experienced by the users, and from the participants' comments and suggestions. According to Tesler the formal comparison served primarily to help in the discipline of systematizing observations. Difficulties were then either taken back to the design team for immediate alterations and retest, placed on a wish list for later solution, or ignored for practical reasons. Iterating this step every time an interesting design question arose, and after every significant milestone in the interface development, required running only about two dozen subjects per week through trials of the system, and caused almost no delay in the total development process since the fixes were made concurrently with the normal course of programming. This whole procedure strikes me as exemplary, as do the somewhat more elaborate and ingenious techniques utilized by Gould, Boies, Levy, Richards and Schoonard (Cox and Cairns 2008).

3.3 Case Studies - Literature Relating to Chosen Methods

This research is user-centred. It is therefore based entirely on case studies. It is important to highlight the goals of HCI case studies (Lazar, Feng, and Hochheiser 2010) (Cox and Cairns 2008) and the role they play feeding straight into interaction design research:

- **Exploration:** Case studies provide valuable feedback in understanding novel problems especially in the early phases of the research. Results often set the foundation for further investigation to inform new system design.
- **Explanation:** Case studies of tools are used to understand a context

[3]Tesler, cited (Cox and Cairns 2008)

of the proposed technology. It is very common in computer systems that study participants use the technology in unexpected ways that were not considered in the initial design which impacts the iterative design loop (Klasnja, Consolvo, and Pratt 2011).

"As HCI researchers often use a case study as a tool for understanding the technology usage and needs of populations of potential users, HCI case studies often largely draw upon representative users and use cases, omitting extreme cases." (Lazar, Feng, and Hochheiser 2010)

- **Description:** Descriptive case studies are longitudinal and in-depth case studies. They contribute to documenting a system, a context of technology use, and the process that led to a proposed design. They are particularly useful for technology involving new design methodologies. In interaction research, the process behind the design is usually the focus of the case study. "Case studies that describe design processes and results have been written for a wide variety of topics in HCI, specifically for participants with impairments." (Lazar, Feng, and Hochheiser 2010) (Cox and Cairns 2008).
- **Demonstration:** Demonstrative case studies are shorter and less in-depth than descriptive case studies. Their purpose is to show how a new tool was successfully used. Participants demonstrate the effective use of a new tool to complete one or more assigned tasks.

Case studies in this research will be of two types: Demonstration case studies followed by descriptive longitudinal and in-depth case studies.

3.3.1 Demonstrative Case Study

A good example is a case study conducted by Shinohara and Tenenberg (Shinohara and Tenenberg 2009) of a blind person's (Sara) use of assistive technology. Sara's case study focused on one person's use of technology. How a blind person might use a variety of assistive technologies to achieve tasks, user interactions, including failures and response to those failures.

In this case study, Shinohara and Tenenberg (Shinohara and Tenenberg 2009) used three types of technology biography[4]: "demonstrations of de-

[4]Blyth and Mon and Park, cited (Cox and Cairns 2008)

vices (technology tours), reflections on memories of early use of and reactions to devices(personal histories), and wishful thinking about possible technological innovations (guided speculation)" (Shinohara and Tenenberg 2009). Data sources used in this study demonstrate three types of case study data: "artefacts, observation, and interviews" (Shinohara and Tenenberg 2009).

A total of 12 hours was recorded in Sara's home, broken down into six, two hour sessions. Raw data consisted of written notes, audio recordings, interviews and photo documentation. Twelve tasks were defined and recorded in terms of their goals. The insights from the individual tasks guided the design of improved tools (Shinohara and Tenenberg 2009).

Although Sara does not provide a comprehensive picture of the needs and concerns of all blind people, the investigations of her needs and goals led to valuable insights that might apply to many other blind people. The Shinohara and Tenenberg (Shinohara and Tenenberg 2009) case study helped the researchers to understand how Sara used a variety of technologies to accomplish multiple tasks. They were specifically interested in understanding "what technologies were most valued and used, when they were used and for what purpose" (Shinohara and Tenenberg 2009). Conducting the study in Sara's home helped the investigators gain insights into how she actually addressed real challenges, as opposed to the more engineered results that might have been seen in the lab.

Sara's case study demonstrates four key aspects used to describe case studies for users with impairments. These points align with my research methods and will be followed as guidelines in the case studies of my research:

- In-depth investigation of a small number of cases: In-depth, broad examinations of a small number of cases are used to address a vast range of concerns.
- Examination in context: Labs have the advantage of removing undesired external influences which is not a realistic or credible environment to show how the technology would work. On the other hand, single case studies conducted in a realistic context give meaningful results which are applicable in the real world and are more informative than large scale case studies conducted in a lab.

- Multiple data sources: Known as data triangulation and is especially important in single case studies. Multiple data sources are combined to validate the evidence and the quality of the data. Contradictions are important too because they compel the researcher to dig deeper, consulting new data sources, which is the essence of grounded theory and action research.
- Emphasis on qualitative data and analysis: Question of how the technology was used to achieve an assigned task are more important than how long it took to complete it. Researchers focus on the quality of the system in successfully delivering what is was designed for rather than the system speed.

It is important to highlight that although single case studies can be very informative about the success of a system, results cannot be generalized to include all members of user criteria especially in disability. The real value of single case studies lie in creating realistic insights into design challenges which can be applied to a broader scale of users.

"Sara's case study led to some suggestions for the design of assistive devices that would help Sara with her daily challenges, but could go further, to influence insights that apply to many blind people. As a result, designs might be useful to a much broader range of blind users." (Shinohara and Tenenberg 2009)

The goal of Sara's case study was: a deeper understanding of a blind user's use of assistive technology in her home. Similarly, usability case studies in this research will have a centre goal of understanding speech disabled participants' use of the data glove and how effective it is in facilitating their daily communication and interaction within a public setup.

3.3.2 Descriptive Longitudinal and In-Depth Case Study

In depth case studies executed in-context, in realistic environments, present credible and valuable evidence. Careful consideration is given to the selection criteria of case study participants. Analyzing the data from the case studies and further interpretation is of the upmost importance[5].

[5] Yin, cited (Lazar, Feng, and Hochheiser 2010)

In these studies, the process of developing a new system or interaction technique is more important than the end product, especially for innovations that tackle new challenges in the context of use (Cohene et al. 2007).

A study at the University of Toronto (Cohene et al. 2007) provided the base for a very interesting single in-depth case study involving the design of an assistive technology tool to help people with Alzheimer's disease. "This project was based in a body of prior work that firmly established the importance of reminiscences for people with Alzheimer's disease." (Cohene et al. 2007) The goal of the case study was to develop a multimedia tool to help people with Alzheimer's disease recall and relive old memories. The sole participant of the case study was a 91 year old woman named Laura. Laura and her two daughters were fundamental in the study which focused on developing a system to help Laura with her memory (Cohene et al. 2007).

The study started with an exploratory phase to understand Alzheimer's disease challenges faced by patients and their families. A broad understating of the disease was necessary even though the study was aimed to develop a tool specifically tailored to the needs and abilities of Laura. Researchers' observations resulted in a comprehensive understanding of the "abilities and impairments of the participants, leading to a set of design principles" (Cohene et al. 2007). The study also included feedback from caretakers and therapists which acted as a basis in outlining a set of guidelines to assist with memory recollection. As part of the study, family members were required to complete a "family workbook" accumulating stories in the form of pictures, videos and music. The collected media was to be included in the tool the researchers were working on developing, with the main purpose of helping the study participants with Alzheimer's disease remember. The tool was developed through a series of prototypes which lead to an interactive multimedia device informed by the system whit output displayed on a screen. The prototypes were refined based on the feedback of the study participants during eight testing sessions over a period of four weeks (Cohene et al. 2007).

The research team conducted follow-up interviews with family members which confirmed that the system contributed in enhancing the memory of the participants.

“This project as a whole is an exploratory case study. As relatively little work has been done on user interfaces for people with Alzheimer’s disease, the description of a successful process is valuable in and of itself” (Cohene et al. 2007). The proposed design served to generate further investigations rather than as a solution.

It is very hard to generalize when it comes to disability and especially a cognitive one like Alzheimer’s disease. Researchers on this case study aimed at extending the applicability of this work by scaling the design process to include more participants to improve the tool (Cohene et al. 2007).

This research required serious time commitment from all parties involved: participants with Alzheimer’s disease, their family members, and research team members. This, combined with the emotional strain, required intensive resources. Even though the result could not be generalized to other users, the documentation of the design process and the resulting designed tool were considered important contributions (Cohene et al. 2007).

> “The most broadly applicable results from this story lie in the lessons learned. The authors concluded that new design methods and principles were needed for working with individuals with Alzheimer’s disease, that active participation was more stimulating than passive, and that working with both the patients and their family members throughout the entire design process was necessary. Practical concerns included the resource-intensive nature of the research, the emotional commitment required of the family members, the need to make the approach practical for larger numbers of families, and the need for standards for evaluation” (Cohene et al. 2007).

Although drawn from this particular project, these insights might be extremely valuable to others interested in conducting related research. Similar to this study, my research will require working directly with speech disabled participants and children with non-verbal autism. My research dictates interacting with family members, therapists and caregivers of case study participants. Also, through the process of testing and collecting information, I can learn a lot about the nature of the disability and how my design of an assistive tool can help not only the participants but also the broad spectrum of users with similar disabilities making my design proposal universal and accessible to many people.

3.4 Chapter of Research: Study

3.5 Introduction

Assistive technology designed to enable communication for non-verbal disabilities is currently available in the form of software. Special communication apps are used to help speech disabled children communicate via tablets and smart devices. Parents try to limit access to other features on the tablet by locking the device to be used only with the communication app. Through observation while visiting schools and sitting in classrooms, we noted that this causes frustration to the children although it was designed to make their lives easier. we identified a need for a stand-alone device that serves the purpose of communication without offering any other features.

Children with non-verbal autism use a form of sign language called Makaton (Charity 2017). Makaton is a set of action words a child signs to communicate his/her feelings and needs. The focus of the study is to design a hand gesture recognition system to translate Makaton sign language action words to text and speech.

There are two approaches in research for sign language hand gesture recognition. First approach is using computer vision and the second is using data gloves. Computer-vision hand gesture recognition for the purpose of translating sign language relies on cameras for recognition and therefore, must be paired with smart devices to operate. Data gloves, however, have potential to operate independently from a smart device. Consequently, data gloves recognition is the chosen method to translate sign language hand gestures for this study.

A Data glove is a wired interface with certain tactile or other sensory units attached to the fingers or joints of the glove, worn by the user. Tactile switches, optical goniometer or resistance sensors measure the bending of different joints which determine if a hand is open or closed and if finger joints are straight or bent. The orientation of the hand can be described in terms of two orthogonal directions—the facing of the palm, and the direction to which the hand is pointing. These results are mapped to unique gestures and are interpreted by a computer.

Glove based sign language recognition systems have been reported to offer a wider vocabulary and better recognition accuracy than computer vision systems. Nevertheless, the enormity of the sign language library makes it very difficult to find a match within large vocabulary data bases (Premaratne, Nguyen, and Premaratne 2010). Another drawback is the limited manoeuvrability due to wires connecting the gloves to the computer.

In this study, we use a limited vocabulary of ten action words signs using a wireless and standalone data-glove which has sensors placed to monitor the flexing of fingers to get accurate input information of hand gestures. Recognition modules are based on hand shapes and orientation rather than position or dynamic movement recognition. We have simplified recognition in an attempt to reduce the hardware, making the data glove simpler to run, easier to wear and cheaper to produce. In this chapter, we demonstrate how these issues are explored through gained feedback from carers of non-verbal autistic participants about their use of the data glove and how it affected their daily communication.

This study is part of a program to develop and produce an affordable and accessible data glove that translates sign language to text and speech, facilitating daily communications between individuals with speech disabilities and the general public.

3.6 Background

Since the 1980s, computer vision and data gloves have been used to recognize hand gestures for the purpose of translating sign language. Hand shapes are one of the primitives of sign language and reflect the information of hand configuration. They are known to be very stable and can be used to distinguish most signs (Fang, Gao, and Zhao 2003).

Even with advancements in computer vision, glove based sign language recognition offers the widest vocabulary and the best possible recognition accuracy. However, no recent such system has been reported with very high accuracy (Premaratne, Nguyen, and Premaratne 2010), possibly because researchers are more focused on vision based systems.

There are many versions of the data glove that translate sign language to text or speech. Most of these gloves rely on a smart device for output and perhaps none have moved beyond prototyping. There is almost no published work showing evidence of sign language data gloves being tested by speech-disabled participants for daily communication. This is possibly due to the complex programming and hardware required. In this section, we briefly highlight some examples of the sign language translating Data Gloves.

One of the earlier advanced systems to convert gesture to speech was demonstrated by Fels and Hinton (Fels and Geoffrey E Hinton 1993). They used a Data Glove in 1992 to convert hand gestures to speech via a speech synthesizer. Their Glove-Talk vocabulary consisted of 66 root words, each with up to six different endings. The total size of the vocabulary was 203 words. Most of these hand shapes represent the ASL alphabet. They also utilized orientation differences in the hand shapes for semantically opposite words such as "come" and "go" which have a 180 degree orientation difference. Various endings for words were formed through different hand movements.

Liang and Ouhyoung also used the DataGlove to develop a Taiwanese sign language recognition based on Hidden Markov Models (HMM) and integrated statistical approach used in computational linguistics (Liang and Ouhyoung 1998). They utilized specific cues used in Taiwanese Sign Language in order to develop the system. There are 51 fundamental postures in Taiwanese Sign Language. Most gestures mainly contain only one posture, for example, "I", "you", "who", etc., while gestures with multiple postures are also used, such as, "originally", "father", "mother", "thank" and "goodbye".

This system was designed to recognize large set of vocabularies in a sign language by recognizing constructive postures and context information. They had a 250 word vocabulary. It could classify 51 static gestures in 6 orientations. They reported that a user dependent system classifying in real- time with an accuracy of 80%.

In 2011, Oz and Leu developed an American Sign Language (ASL) recognition system based on the Cyberglove^{TM}sensor glove and artificial neural networks (ANNs) to translate ASL words into English (Oz and Leu 2011). The overall structure of the proposed system consists of a sensory glove and a motion tracker. The data stream from these devices is received and segmented by a velocity net- work with noise reduction and feature extraction followed by a word recognition network. The gesture features extracted from the raw data are then sent to a decoder of the recognition system. The final outcome of the system is to produce voice of the recognized ASL words with a speech synthesizer.

Their goal was to continuously recognize ASL signs using the glove in real time. They trained the ANN model for 50 ASL words with a different number of samples for every word and the classification results achieved 90% accuracy which demonstrated that their used successfully for isolated word recognition. They also concluded that some gestures in ASL required that both the right and left hands be manipulated simultaneously by applying the proposed model but with two data gloves and more motion trackers. Although the ANN model was very successful, it never went past the research phase and no plans were made for it to go into production.

Looking at all previous successful work in this field, we were motivated to introduce this technology to the assistive wearables and healthcare innovation markets and give a chance to speech disabled individuals to try it and use it.

3.7 Method

Our system has been programmed to identify a limited vocabulary of ten signs based on ten right hand postures and three orientations using an accelerometer data glove to get accurate input information. Failure to detect/identify the gesture will result in no words being spoken. The accelerometer was also used to differentiate between when the glove is being used to sign or to play. When the glove is static it starts processing. In signs using both hands, only the right hand was programmed. This was effective because in signs using both hands, either both hands are the same or one hand stays motionless in holding one position, while the other hand makes the sign. A good example is dance, where the left hand is static while the right hand motions the sign. Another example is play and happy. In both signs, the right and left hand have the same gesture. Two different conversation scenarios were written for the participants where they can communicate using the ten previously programmed actions words.

Hard coded words were:

- Yes
- No
- OK
- Play
- Dance
- Colour
- Happy
- Hungry
- Eat
- Drink

Two participants with non-verbal autism (boys ages 9 and 12) were recruited. Selection criteria was based on the familiarity with sign language according to attending speech therapists recommendations. The training session consisted of 2 hour long task (described below) and broken into four 15 minute segments. Participants were shown videos of the signs, and trained together with the researcher and their speech therapist. Speech therapists" role was to help the researcher communicate with the participants and provide feedback based on observation. Participants started getting familiar with how the glove worked within half an hour of being introduced to it. Video documentation of the participants using the glove was recorded. Usability feedback from the participants, parents and therapists was noted.

(a) Dance

(b) Play

Figure 3.3: Examples of a test subject making hand gestures while wearing the Data Glove

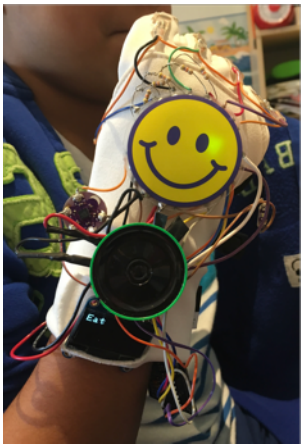
3.8 Task

A dialogue has been drafted between the therapist and the participant for two simple real life scenarios. The therapists would ask the questions and the participant would sign the reply using the data glove. Words appear on the small screen and are spoken out loud through the speaker on the data glove as in Figures 3.3 and 3.4. The therapist would then move to the next line in the dialogue. This dialogue is an example of a conversation speech disabled individuals engage in every day.

3.8.1 Task I - Participant A - Playtime Dialogue

Data glove pre-programmed Makaton sign language vocabulary:

- Yes
- No
- OK
- Play (Verb)
- Dance (Verb)
- Colour (Verb)



(a) Eat

(b) Hungry

Figure 3.4: Examples of a test subject making hand gestures while wearing the Data Glove

- Happy
- Hungry
- Eat (Verb)
- Drink (Verb)

Script:

Hello! So what are you doing? How was your day so far?

[...Conversation progresses...]

Let's do something else? What would you like to do?

[Subject replies with an activity]

Really you like to *[insert activity]*?! Do you have any ideas?

[Subject mimes one of the sign language activities]

And how does that make you feel?

3.8.2 Task II - Participant B - Restaurant Dialogue

Data glove pre-programmed Makaton sign language vocabulary:

- Yes
- No
- OK
- Happy
- Hungry
- Eat (Verb)
- Drink (Verb)

Script:

Hey, do you want to go to a restaurant?

Yes

Cool, let's get going!

What will you order?

[Subject replies with food item]

Do you want to use the bathroom before we go?

[Yes/No]

3.9 Feedback

Performance feedback was very good, where 4 out of 5 attempts resulted in accurate output. Majority of feedback mainly related to power issues where the glove sometimes got stuck or didn't respond when the battery was running low. Occasionally, the glove had major delays. Battery lasted about two and a half hours.

Feedback from participants was conveyed through observation and communicated by their therapist. This method is generally used in studies, where users are unable to communicate, or are unable to process information due to their impairment (Lazar, Feng, and Hochheiser 2010) in which case, caregivers and family members were used as the primary information source.

The participants' feedback was mostly related to glove design and hardware enclosure. Participants expressed that the glove was bulky and felt a little intimidated by the exposed wires. They felt that the glove was uncomfortable to wear and had difficulties bending their fingers. Sometimes glove delays caused frustration amongst the participants because they thought it was their fault. Video documentation took so long that it started to look like it was rehearsed at the end.

The researcher's observation was that participants wanted to use the glove for other things while wearing it, like playing or holding things[6]. This affected the output of the glove and programming had to be revisited during the testing phase. A quick solution to get through the testing session was to set the glove to process gestures only when the accelerometer registered an upright position. Other solutions will be discussed below.

3.9.1 Results

The testing demonstrates that the system is capable of translating sign language to text and speech with an accuracy rate of 80-85%[7] and about 15% of attempts resulting in no words being spoken due to failure to detect the gesture. Reasons for failed attempts is due to the fact that signs vary in time and speed, even with the same user, where slight changes of speed and position of hands occur (Premaratne, Nguyen, and Premaratne 2010). Also, the similarity between some signs sometimes makes it difficult to distinguish them. The fact that the users were playing and signing at the same time while wearing the glove added to this confusion.

Another factor that affected the results was that participant B had lower motor abilities and therefore was not able to bend his fingers all the way. This threw the glove off recognition ranges for some gestures.

3.9.2 Conclusion

A revised design is being developed based on the feedback of this study.

[6] As in Figure 3.4

[7] Testing video URL: https://youtu.be/imf5JiCfGrc

Improvements include design, hardware as well as software reconfiguration.

Design:

Exposed hardware was very intimidating for the children and discouraged them from using the glove.

Glove design has to be revised to be more user friendly. Hardware enclosure has to be redesigned and embedded in the textiles. Custom glove pattern is underway to house the sensors in channels and enclose the hardware in the inner lining of an improved glove design. This new design insures that the circuit is protected as well as insulated from skin contact. Stretchable fabric will be used to make finger movements more flexible and insure easier bending of fingers for small children and children with weak motor development which is common in autism. For safety, fireproof, non-conductive material will be used to house the circuit and insulate the glove.

Hardware:

Tugging wires was a major issue in this study.

The Hardware needs to be further reduced and enhanced. The Arduino Lilypad™micro-controller is to be replaced by Raspberry Pi Zero. This will further reduce the cost of the hardware to half as well as enhance the performance and battery life. Raspberry Pi also has a built-in text to speech synthesizer which will allow us to eliminate the Emic2 text-to-speech chip from the circuit making the glove more usable. It would also reduce the cost significantly. The accelerometer will be replaced with a gyroscope. A gyroscope will expand feedback from angles and orientation to cover full gesture motions in the 3D space, giving us more data to process and the ability to recognise dynamic gestures.

I would also like to:

- Add a button to switch between training mode and pre-programmed mode.
- Add a button to tell the glove when to process for children who want to keep wearing it.
- Make all hardware removable from glove to be able to wash it.

- Encapsulate circuit to make it water proof.
- Equip the glove with a BLE (Bluetooth^{TM}Low Energy) chip to provide connectivity with a smart device for training mode.

Software:

Delays in processing was due to the variance in hand gestures between the pre-programmed signs the signer's abilities. Errors occurred because the glove was being used for other activities and didn't have an indication of when to start or stop processing.

Make the software personal to enhance accuracy is to propose a training mode. Training mode would enable users to upload their own sign language mapped to their individual motor abilities. For that, the glove needs to be paired with machine learning software to store and output gesture classifiers. Enabling users to upload their own version of sign language makes this data glove accessible to everyone who needs it regardless of which sign language library they use. It will also allow children who do not follow a standard sign language library to customize their hand gestures and be able to communicate with the general public, who are unfamiliar with sign language.

Pair with IBM WATSON^{TM}APIs for speech translation to other languages. This would make the glove universal and usable in any country breaking yet another language barrier.

3.9.3 Future Work

Based on engagement in the field and taking part in various assistive technology events, it has become evident that there are many different application to the data glove which was designed for this study.

Data gloves for Sign language communities:

- Hearing impaired or hard of hearing can use this data glove for their daily communication.
- Empowering professionals with speech disabilities/hearing impairments to conduct meetings, give talks, or go on business trips without the

need to hire a translator/interpreter.

- Enabling children with non-verbal disabilities to interact with their peers in integrated classroom.
- Stroke survivors who have limited motor abilities and are not familiar with sign language can train the glove to customised hand gestures.
- This glove can also be used as an educational tool to teach children sign language.
- Accessibility units at airports can utilise the glove for it"s translation features.
- Companies who wish to make to transition to become fully inclusive can provide the glove to enable their employees who have speech disabilities.

Data Glove applications in other fields:

Data Gloves are no longer limited for use in computer human interaction. While some Data Gloves are designed for interacting with a computer for gaming and other natural like communication, other Data Gloves are used primarily for 3D motion capture in the motion picture industry as well as some being used for healthcare applications such as the monitoring of vital signs, to physiotherapy on injured or healing hands and fingers (Premaratne, Nguyen, and Premaratne 2010).

Today, ASL and many sign languages around the world see continuously being interpreted using either vision (with and without markers) or glove based systems as new technology develops. This trend will continue until it results in a highly reliable system in which, the mute and deaf would feel more natural to express their feelings like their able counterparts (Pavlovic, Sharma, and Huang 1997).

Chapter 4

Brief Overview of the Next Study

Based on the feedback we got from the initial study, we have developed a second glove prototype employing solutions suggested in the results of previous usability testing.

4.1 Data Glove Prototype II

The second iteration of the glove has improved in hardware, software performance, design and cost[1].

- **Hardware:** Raspberry Pi Zero with an embedded circuit, speaker, OLED screen and power supply all on one board.
- **Software:** Machine learning employed to allow each user to train the glover to their own version of sign language and to their personal motor ability. Speech output can be set in any language.
- **Design:** All hardware embedded in special channels sewed in the lining of the glove. Circuit is insulated with non-conductive and fire resistant fabric. Circuit is removable to enable washing of the glove. Glove fabric is stretchable and soft.

[1] As seen in Figures 4.1 and 4.2

Figure 4.1: Data Glove Prototype 2

Figure 4.2: Data Glove Prototype 2 Features

(a) Participant A (b) Participant B

Figure 4.3: Examples of a test subject making hand gestures while wearing the Data Glove

- **Cost:** Hardware cost was reduced by half. Design cost increased because the glove was custom made. Software had to be paired with cloud computing web application which requires an ongoing subscription.

Testing was done with two different groups of users and in two locations:

4.2 No Barriers Summit: Innovation Village, Lake Tahoe, June 2017

No Barriers Summit is an annual event bringing together assistive technology and individuals with different disabilities to interact with the technology in an open four- day exhibition. I was invited to give a talk about my data glove and showcase it in the exhibition. The data glove was used by a number of adults with speech disabilities, hearing and visual impairment[2].

The task was to demonstrate, to one participant at a time, how to record

[2] As in Figure 4.3

custom sign language hand gestures. The participant then puts on the glove, presses the record button, makes a dynamic hand gesture, then saves the gesture under a name of their choice. Next, the participant chooses a language from a drop-down menu for the output speech. Finally, the participant makes the same dynamic hand gesture he has recorded and a word is displayed on the screen and spoken out through the speaker in the language selected[3].

We had seven participants who were patient enough to go through the 20 minute process. Accuracy rate was 100% with no errors. This is because the glove is being trained and tested by the same person, so the errors that occur because of hand gesture variations were eliminated in this incident.

Participant reactions varied between amazement, and feeling enabled. They had a sense of achievement when they trained the glove and the output was accurate.

Observation revealed that the participant with visual impairment did not know which buttons to press, buttons were colour coded. Connectivity to the web application (where the machine learning happened) was very difficult using a public network so we had to keep the glove connected to the computer via a wire, although it was designed to operate as a stand-alone device. Also, there was no feedback on the glove that informed the participant of which mode the glove was on, training, classifying or processing.

Direct feedback from several participants suggested that they prefer keeping eye contact while signing and don't have a use for the screen. Although the screen is not essential for communication, we feel that it confirms to the hearing-impaired signer that what he is signing is indeed what is being spoken out through the speaker. This feature was especially useful when I used the glove to sign to a Korean crowd and set the speech out to Korean and didn't understand the speech.

[3]Testing video URL: https://youtu.be/lILyrpKAIh0

4.3 Charlton Park Academy: Communication Works, London, July 2017

Charlton Park Academy is an inclusive school for children with different needs. Most of the students in the school need assistive technology to communicate. I was invited to give a talk about my data glove and to showcase my data glove in an exhibition for assistive technology called “Communication Works” amongst a wide range of assistive technology designed to enable communication. Tablets with special communication apps were on show and cost a minimum of £2K to £9K with a monthly subscription. The impact of the talk was positive and I had queue of parents requesting to include their children in the glove studied. Parents expressed that they are interested in acquiring the data glove for their children.

When asked about what their children currently use and what were the drawbacks, most parents had similar responses. All children with non-verbal disabilities in the school used special tablets with communication apps. Parents’ main concerns were: having to limit the use of tablets with their children, resorting to lock the tablet to restrict its use to the communication app which causes frustration to the children. Another disadvantage was that children don’t learn how to sign or have eye contact while interacting with the public. They hide behind the screen and often keep their eyes low or fixated on the screen.

4.4 Discussion

Collating feedback from both events, an outline for the next prototype has emerged. Main issues to be addressed:

To add feedback on the glove to inform users of the three different software states: Record, Train, Save. Feedback will be in the form of text appearing on the screen attached to the glove.

To solve connectivity problems by adding a mobile module with a chip or a Bluetooth™Low Energy (BLE) to replace WiFi™.

Change buttons to be different shapes rather than different colours to cater to the needs of visual impaired individuals.

Design a custom PCB with arm processor, built in text to speech synthesiser, speaker and screen. Consider circuits used for wearable technology; such as flexible circuits, printed circuits and embedded censors.

Power supply with narrow band technology to reduce power consumption especially if a GSM/SIM chip is added to the circuit. Mobile modules require power to connect and consume energy to maintain connectivity.

Chapter 5

PhD Timeline

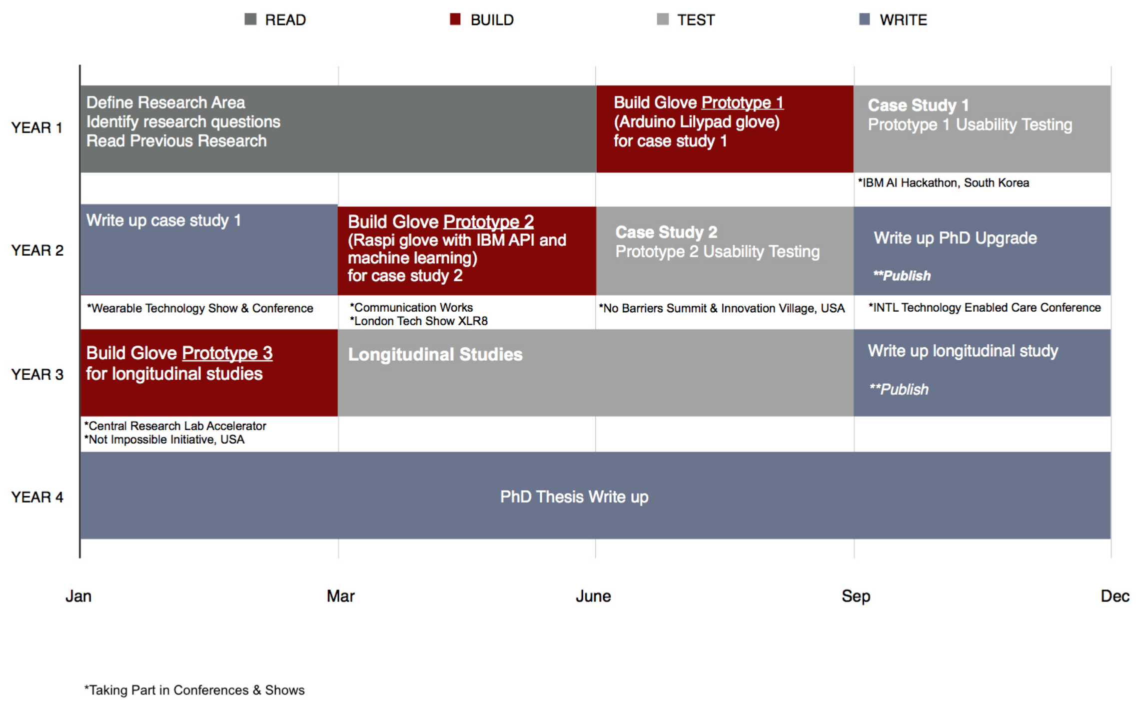


Figure 5.1: PhD Timeline Overview

Chapter 6

Research Impact and Social Engagement

6.1 Awards

- Central Research Laboratory Hardware Accelerator Sep 2017 to February 2018
- Wearable Technology Save the Day Award for Social Impact, November 2017
- Grand Prize Global IBM Hackathon In Artificial Intelligence for Social Care, Seoul South Korea 2016
- Innovation Award, The Wearable Technology Show & Conference, London 2016, shortlisted 2017
- Innovation & Entrepreneurship Prize for Graduate students in the UK, London 2015
- Shortlisted Not Impossible IOT Humanitarian Award, Las Vegas January 2018

6.2 Speaking and Exhibiting

- IBM Global AI Hackathon for Social Care, Seoul December 2016

- Wearable Technology Show, London March 2016, March 2017
- No Barriers Summit & Innovation village, Lake Tahoe California, June 2017
- London Tech Show XLR8, London June 2017
- Communication Works, Charlton Academy, London May 2017
- International Technology Enabled Care Conference, Birmingham, October 2017

6.3 Community Engagement & Talks

- The Institution of Engineering and Technology, London November 2017
- The Guardian panellist for Artificial Intelligence debate October 2017
- Financial Times Tech Talk London August 2017
- Women in Tech London May 2017
- Greenwich Autism Alliance Foundation
- Charlton Academy for students with low incidence special educational needs
- Royal Association for Deaf People

6.4 Media Features

- BBC Technobabble
- Discovery Chanel Canada
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