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Evaluating touchless capacitive gesture recognition as an assistive device for upper extremity mobility impairment

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Abstract

Introduction: This paper explores the feasibility of using touchless textile sensors as an input to environmental control for individuals with upper-extremity mobility impairments. These sensors are capacitive textile sensors embedded into clothing and act as proximity sensors.

Methods: We present results from five individuals with spinal cord injury as they perform gestures that mimic an alphanumeric gesture set. The gestures are used for controlling appliances in a home setting. Our setup included a custom visualization that provides feedback to the individual on how the system is tracking the movement and the type of gesture being recognized. Our study included a two-stage session at a medical school with five subjects with upper extremity mobility impairment.

Results: The experimenting sessions derived binary gesture classification accuracies greater than 90% on average. The sessions also revealed intricate details in participant's motions, from which we draw two key insights on the design of the wearable sensor system.

Conclusion: First, we provide evidence that *personalization* is a critical ingredient to the success of wearable sensing in this population group. The sensor hardware, the gesture set, and the underlying gesture recognition algorithm must be personalized to the individual's need and injury level. Secondly, we show that explicit feedback to the user is useful when the user is being trained on the system. Moreover, being able to see the end goal of controlling appliances using the system is a key motivation to properly learn gestures.

Keywords

Capacitor sensor array, wearable computing, e-textile, gesture recognition

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Introduction

Technological miniaturization and low-power systems have precipitated an explosive growth in capability and adoption of wearable sensors. These sensors can be applied to many medical and rehabilitative applications, including physiological monitoring,[1] telemedicine,[2] rehabilitation compliance,[3] and assistive input.[4] The prevalence of such systems has increased to the point that wearable sensors and systems have become a major fixture in medical rehabilitative and assistive devices and are poised to change the way that medical practitioners interact with patients.

However, wearable sensors face issues with maintaining patient compliance. If the patient chooses not to wear these devices, then no intervention can take place on the person's behalf. Therefore it is critical that compliance issues are addressed by either reducing the burden of patient instrumentation or creating an

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incentive for the user to wear these systems. To address the former, building sensors directly into a user's clothing or environment can greatly reduce the burden of instrumentation, and provide a more seamless interface in which to gather and actuate on collected information. E-textile systems solve this by using textiles as the sensors themselves. For instance, Project Jacquard[5] from Google Research is an industry project with the goal of creating fabric sensors embedded into day-to-day clothing.

Assisting a user to perform tasks addresses the issue of creating an incentive to wear such systems. These sensors can then be used to provide input for applications such as environmental control and home automation. These kinds of sensors have immediate impact as an accessibility tool, especially to those with upper-extremity mobility impairments. Persons with this diagnosis, whether the result of a disease or injury, often require wheelchairs for mobility. Depending on the severity of the motor impairment, a user may require systems and sensors such as the sip-n-puff,[6] eye gaze tracking, or electroencephalography (EEG) monitoring[7] as an assistive interface to facilitate input. Sensors built into clothing or into the environment such as bedsheets or wheelchair pads can act as a simple and nonintrusive input for gesture recognition, facilitating additional interaction patterns for individuals with these kinds of disabilities.

Designing a wearable gesture recognition system for upper extremity mobility impairment is a difficult and multifaceted problem. First, the amount of mobility that a person has is highly dependent upon the type of injury or disease which precipitates the mobility impairment. A stroke may remove fractionated movement (ability to control specific portions of a limb) or somatosensation (feeling), while a complete spinal cord injury removes all neurological functions below the injury site. Second, there is large variation in injury levels and hence, the degree of limb mobility that a user may have is highly variable. A person with a C6 spinal cord injury may maintain the ability to pronate their forearm, while a person with a C4 spinal cord injury may lose all or most motor function involving the arms. Third, within the same injury level or exact diagnosis there exist a broad range of exact motions a person is capable to perform and what they have relearned through rehabilitation. Finally, even considering all of these other factors to be held even, there remains large variation in hand postures, body build, and limb reachability, all which could potentially affect the best position to place an assistive device. **For these reasons, it is critical that the assistive device conforms as much as possible to the mobility profile of the individual user.** With this requirement in mind, this paper asks and addresses the following question: **What underlying principles should govern the design of sensors built into clothing for gesture recognition and environmental control for individuals with upper extremity mobility impairments?**

This paper aims to highlight the primary challenges through a clinical study addressing the use of textile wearable sensors as an accessibility tool for people with these types of motor impairment. Our custom sensor, illustrated in Figure 1 is an array of conductive textile plates sewn into fabric such as denim jeans. The flexible sensors can also be built into items of daily use such as wheelchair pads, bedsheets, and pillow covers using embroidery. The sensors capture movement in its proximity and work on the principle of change in capacitance. A user wears the sensor array and performs gestures in the proximity of the sensor. We focus on an alphanumeric gesture set based on EdgeWrite.[8] The system uses a position tracking and dynamic time warping (DTW)–based signal processing algorithm that converts the raw capacitance measurements to an alphanumeric gesture. Each classified gesture can be used to control appliances in a home setting. We perform a usability study of the wearable sensor on five individuals with C3–C6 spinal cord injuries. Figure 1 demonstrates our experimental setup. The cameras and accelerometer-enabled smartwatch were used to capture groundtruth and baseline data for the system setup. We use a custom visualization to provide feedback to the user on how they are performing the gesture

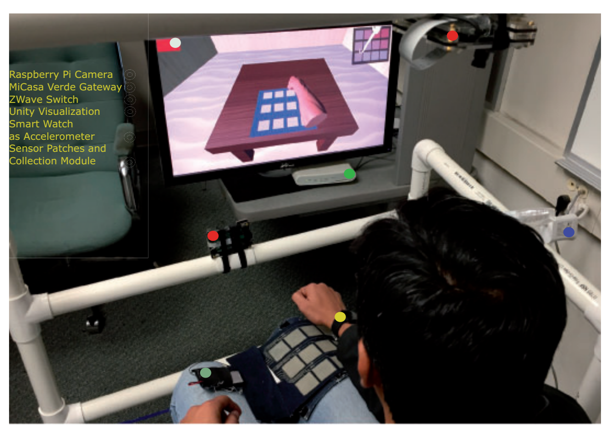

Figure 1. The figure shows our prototype system and experimental setup demonstrated by a subject. The system is composed of a four by three capacitive sensor array sewn into the denim fabric using conductive wires. The data from the sensors are analyzed using our custom-designed wireless module, which uses capacitance measurement ICs, an MSP430 micro-controller, and Bluetooth wireless module. It also demonstrates the Smartwatch accelerometer, which was used to profile gestures for confidence and intensity. The visualization demonstrates two kinds of feedback; instantaneous positional data, and post-gesture classification.

and how the system is recognizing the gestures. The system was evaluated in a multiday study in a medical school setting.

Our study builds on related work on assistive technology and user studies that evaluate assistive technology. Here we compare and contrast our work with the most relevant literature.

Assistive technology: Assistive technology is a field that includes the use of any tool that enables a user to perform a task that would be otherwise difficult or impossible. This means that assistive technology can be as simple as a "Mouth Stick" for various pointing exercises,[9] to a complex system such as EEG-driven wheelchairs[10] or electromyogram (EMG) prostheses.[11] Gesture recognition in assistive technology has been considered in recent years, including head gesture control of wheelchairs[12] and smart interfaces to assist individuals with cognitive disabilities.[13] Recent years have seen the growth of wearable sensors such as wrist-worn accelerometers, wrist bands, and headgear for gesture recognition. More recently there is a surge of systems where sensors can be built into items of daily use such as clothing[5] for gesture recognition. While most of these systems are touch-based, our textile sensor system is touchless and uses change in capacitance to measure movement in the proximity of the sensors.[14] Touchless sensing is critical for the considered population where users often experience limited sensitivity to their periphery and continuous touch can lead to skin abrasion. This paper explores the feasibility of using touchless wearable textile sensors built into clothing for gesture recognition in individuals with limited mobility.

User studies on assistive devices: Assistive technology cannot be developed completely in laboratory environments. The devices themselves are meant to apply to specific populations, and therefore must be tested rigorously within that population. Thus, user feasibility studies and evaluations have been performed to evaluate assistive technology for multiple populations including cerebral palsy[15,16] dementia,[17] aging-in-place,[18] and spinal cord injury.[19] Motor learning for individuals with mobility impairments has been studied for rehabilitation purposes. Amongst the salient conclusions drawn is the importance of controlling feedback.[20,21] Additionally, the use of virtual reality has been considered for rehabilitation of upper-extremity impairment.[22] Our study considers individuals with upper-extremity mobility impairments as a result of spinal cord injury to the cervical vertebrae. These individuals are typically wheelchair users and use our wearable system for environmental control in a smart home. Our goal is similar to the usability studies performed on various assistive care devices. Through our system, our aim is to draw fundamental elements that must be considered in the design of the sensor hardware and software, as well as the feedback mechanisms for learning purposes.

Materials and methods

In our study, we use an array of textile capacitive sensors built into denim fabric. The sensor array can be placed on a subject's thigh or built directly into clothing. The array used for the experiment is composed of three rows of four sensors. Each sensor is one square inch (1×1). The outside of the array measure 6.5 in. by 7 in., with the sensors spaced equidistant from each other. The metallic textiles couple electrically with the body of the user such that hand gestures performed in the vicinity (within a few centimeters) of the sensor array are captured by the system. We use a hierarchical signal-processing algorithm to convert raw capacitor values to gestures. The on-body data-collection module performs gesture classification through two steps: (1) The raw capacitor values are converted to a two-dimensional projection of the geometrical centroid of the hand onto the capacitor sensor array (CSA) and (2) a pattern matching algorithm based on dynamic time warping[23] to classify the gesture. This study focuses on interpreting alphanumeric gestures based on the EdgeWrite gesture set.[8] A full write-up of the system is available in our previous work.[24] Below we briefly describe the tracking algorithm.

Hand tracking algorithm: The two-dimensional position of the hand is calculated as a linear weighted summation of sensor positions for any number of sensors (N), multiplied by their capacitance (c). This acts as a spatial centroid of capacitance which is used to estimate two-dimensional positions as ($\hat{x}$,$\hat{y}$) by the following equations:

$$\hat{x} = \frac{\sum_{i=1}^{N} c_i x_i}{\sum_{i=1}^{N} c_i} \tag{1}$$

$$\hat{y} = \frac{\sum_{i=1}^{N} c_i y_i}{\sum_{i=1}^{N} c_i} \tag{2}$$

Gesture classification: Gestures are segmented in real time by comparing the sum of the capacitor sensors against a threshold T_l. A gesture is inferred as each ($\hat{x}$,$\hat{y}$) tuple calculated from equations (1) and (2) while $\sum_{i=0}^{N} C_i$ is less than T_l. If a gesture is exceedingly short or long, then it is rejected as an inadvertent gesture. The remaining gestures are then classified using DTW,[23] a distance-based vector quantizer, by comparing against a set of training gestures called the codebook. The algorithm is described in Algorithm 1. DTW uses dynamic programming to create the smallest sum distance between two time series by compressing or dilating time.

Algorithm 1. DTW (O, M)

Input: $O = [(x_1,y_1),\ldots,(x_n,y_n)]$ (positions for the gesture) $M = [(x'_1,y'_1),\ldots,(x'_n,y'_n)]$ (model positions for the gesture)
Output: d (warped distance),
$d(0,0) = \texttt{distance}\ (M(1),O(1))$
for i: $= 1$ **to** len(O) **do**
  $d(i,1) = d(i-1,1) + \texttt{distance}\ (M(1),O(i))$
end for
for j: $= 1$ **to** len(M) **do**
  $\mathrm{d}(1,\mathrm{j}) = \mathrm{d}(1,\mathrm{j}-1) + \texttt{distance}\ (M(j),O(1))$
end for
for j: $= 1$ **to** len(M) **do**
  for i: $= 1$ **to** len(G) **do**
    $d(i,j) = \min_{ij} d[d(i-1,j-1), d(i-1,j), d(i,j-1)]$
    $+ \texttt{distance}\ (M(j),O(i))$
  end for
end for
return $d(n,m)$
Complexity: $\mathcal{O}(n \times m)$

Experimental setup: To analyze how each subject performed the gestures, a set of several input devices was used. Figure 1 demonstrates the setup that was utilized in the trials. Our fabric CSA was used as a positional localization system to detect and recognize gestures in a very low power manner. Two cameras were mounted, which would capture two views of the gestures; the distance of the hand from the CSA, and the x–y location of the hand with respect to the CSA. These two parameters are important in the calculation of the position of the hand by the CSA device. A Sony SmartWatch is used to capture the accelerometer values of the hand which was used for performing gestures. A virtual reality system built in the Unity framework[25] demonstrates instantaneous feedback to the user. This feedback is given in two forms, a 3D tool that shows the motion of the arm as it performs the gesture, and a 2D tool that demonstrates the user's calculated $(\hat{x},\hat{y})$ positions. Finally, we use the gestures to control an off-the-shelf Z-Wave home automation system. Specifically, we used the home automation system to control lights, televisions, and fans.

User study trials

Our experiments were performed with five individuals who have spinal cord injuries. Identities of the subjects were anonymized and the subjects were compensated for their time. This study was approved by the University of Maryland Institutional Review Board (HP-00060811). All participants signed informed consent. The participants were males, right-hand dominant with age ranging between 24 and 50 years. The demographics of the subjects in the study is shown in more detail in Table 1, which provides the injury site, the American Spinal Injury Association Impairment Scale classification,[26] the mode of transportation that they most commonly use, and time since the injury at the date of the user study. Each subject participated in two sessions, with each session containing several phases. The first session consisted of four phases; a training phase, an examination phase, a testing phase, and a recall phase.

During the training phase, the user became comfortable using the system by moving their hand around above the array and watching the virtual reality application demonstrate the position extraction calculated by the system. The user then learned each gesture in the set of gestures defined by $G_c \in \{A,B,C,D,E\}$ and depicted in Figure 2, where each gesture is defined by the alphanumeric character which it approximates. To be trained on a gesture, the user must correctly perform each gesture five times in succession on two different occasions. The virtual reality application was used to provide instantaneous positional feedback as well as post-gesture classification (e.g., "Gesture A") feedback.

During the examination phase, the user was presented a set of five gestures in random order, and the user must perform three sets correctly to verify that the user is trained on the system and gestures. No instantaneous feedback was provided, but the user was given feedback on classification through verbal instruction.

The testing phase consisted of the user selecting three gestures from the set of five gestures, and relating them to the three home automation components. For instance, a user may choose to relate "A" to activating and deactivating the fan. They then are presented 150 home automation commands in random order, and

Table 1. Demographic information of users in study.

User	Level/type of injury	Transportation	Age	Since injury	Hand	Pointer
1	C6 complete ASIA A	Manual chair	40	6 months	Right	Finger
2	C5-6 complete ASIA A	Power chair	45	8 months	Right	Side of hand
3	C4 incomplete ASIA C	Power chair/walker	29	5 months	Either	Fist
4	C5 complete ASIA A	Power chair	24	8 months	Right	Fist
5	C7 complete ASIA A	Power/manual chair	38	12 months	Either	Palm

attempt to correctly control the fixtures using the gestures.

Finally, the recall phase consisted of the user attempting to create two sets of five sequential correctly classified gestures for each of the five original gestures.

The second trial consisted first of another "recall" session where the subjects were not prompted with what the gestures looked like, and were asked to perform the five gestures from the original gesture set. The subjects then were given eight new gestures to learn to complete the set depicted in Figure 2 from the EdgeWrite set, and trained on each of these gestures, again with instantaneous feedback using our Unity 3D virtual reality system. They chose five of these eight gestures, which were then given in a random order until they were able to correctly perform three sets of five gestures correctly. Lastly, the subjects chose three gestures from the complete gesture set, and performed home automation testing until the total time allotted for the session had expired (typically ≈75 gestures). Results of the user study are presented qualitatively in the following section through the distillation of two specific insights, and quantitatively in Table 2 and in Figure 3.

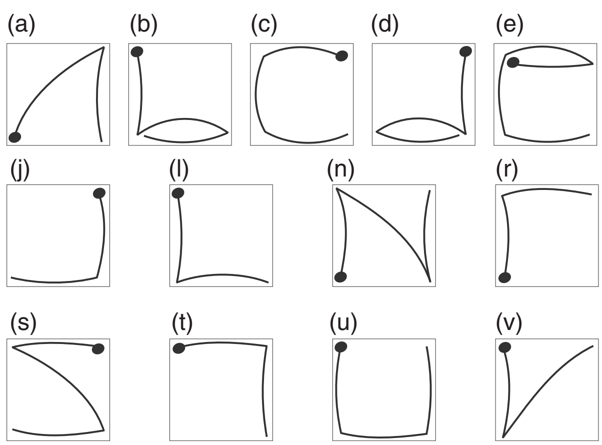

Figure 2. A pictorial depiction of the EdgeWrite[8] gestures used in the user study. Only Gestures (a–e) were used in the first trial, while gestures (j–v) were added to the original set for the second trial.

Results and discussion

Presented below is the raw classification accuracy of the system derived from trials conducted during the user study. The gestures were classified in real time during the study against a set of template gestures, which were created in a laboratory setting. The accuracy is shown in confusion matrix form for each subject in Figure 3 and more granularly in Table 2.

From a quantitative and qualitative analysis of the gestures performed during the user study, we draw two salient insights.

- Personalization is critical to the success of a wearable gesture recognition system. Each individual performs gestures of different sizes, different shapes, and with different speeds. It is a function of the injury level which affects the reach, speed, and way the gestures are performed. Even for an individual the way a gesture is performed varies based on factors like fatigue and motivation. It calls for personalization at two levels: (1) sensor hardware construction and placement on clothing and (2) design of gesture recognition algorithms that adapt to the users.
- Explicit feedback in the form of visualization is important for training: Using controlled feedback through instantaneous and post hoc methods help users learn the gestures faster. It is also critical that the learning occurs in the context of the target application. For instance, in our study we found that our subjects were motivated to learn the gestures when they could use it in the context of the smart home automation system. Our results demonstrate that while sensor hardware and software development is important, a critical ingredient to the adoption of these systems is easy-to-use feedback and training methods.

Using the above insights, we propose algorithms and hardware enhancements for personalized adaptations

Table 2. Accuracy of gesture classification when using a set of template gestures.

	Training and evaluation (% accuracy)					Initial testing (% accuracy)			
User	"A"	"B"	"C"	"D"	"E"	"Testing 1"	"Testing 2"	"Recall 1"	"Recall 2"
1	100	92.5	92.5	100	87	97	100	98	95
2	90	100	100	100	85	90	N/A	98	96
3	100	82	100	100	50	67	90	N/A	92
4	100	92.5	100	86	92.5	90	87	98	98
5	100	92.5	100	100	70	92	93	98	92

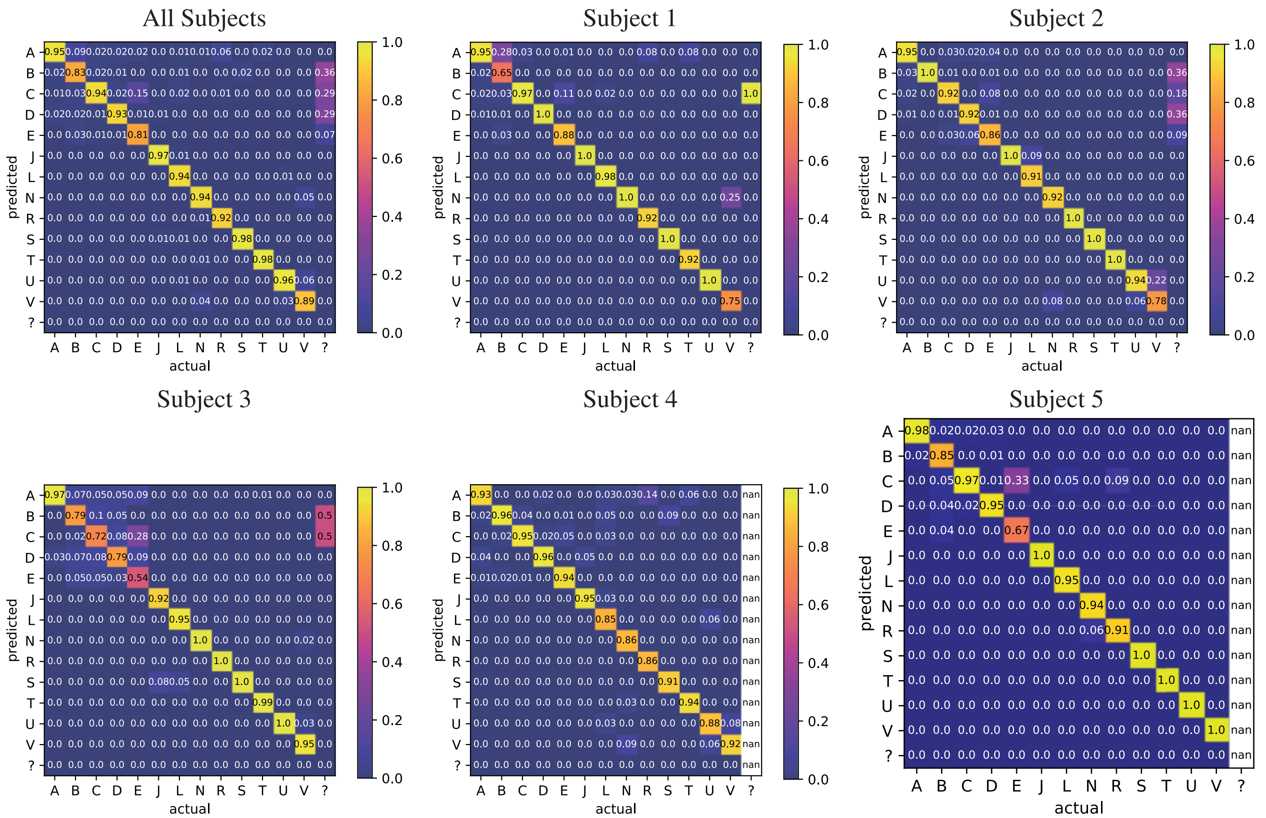

Figure 3. Confusion matrices demonstrating the percentage of classification of each gesture type to the other classifications. Gestures with actual classification of "?" are inadvertent gestures that were classified by the system, and represent a false-positive classification. If a subject had no inadvertent gestures, that column is labeled "nan."

to wearable sensors, and recommendations of feedback mechanisms that the gesture recognition system will benefit from. Our study can inform the design of usable wearable sensors for individuals with limited upper-extremity.

Insight 1: Personalization is critical to the success of a wearable gesture recognition system

While it may seem natural that the inclusion of user preference and ability should be considered in accessible and assistive technologies, many commercial or off-the-shelf devices are not natively configurable, which can lead to device abandonment.[27] Along with rapid prototyping, this fact has led to a dramatic increase in Do-It-Yourself (DIY) assistive technology development.[28] Wearable devices, such as the fabric CSA used in this study, are well suited to use individual configuration for particular users in the same way that clothing can be tailored or fit specific body types.

User-level adaptation: The need for individual configuration became readily apparent as the users began to perform gestures over the array. Each of the five subjects chose to approach the CSA in a unique manner, as is demonstrated in Figure 4.

The exact rotation of the hand has a reduced effect on the operation of a CSA-based system compared to inertial-based systems, as the position tracking is calculated as the centroid of capacitance coupled to the remote body. Fidelity of the position calculation is inversely proportional to the distance of the remote body that is coupled into our CSA and directly proportional to the size of that body. For example, subject 1 does not retract his fingers to make a fist, and instead uses his fingers as a pointer. While the relative area of the body is small (finger compared to a fist), the subject more accurately tracks a specific location very near to the array, as is demonstrated in Figure 5(a).

Conversely, user 3 approaches the array with a fist which is a much larger body, and spreads out the capacitance over a broader area (e.g., Figure 5(b)), but allows a greater distance from the array without losing fidelity. The rotational orientation of the hand with respect to the CSA was typically the palm facing downward, but subject 2 found it more comfortable to have his hand rotated 90°, while subject 5 chose to alternate his palm between facing up or down as his arm would become tired over time. These different hand positions and orientations could potentially reduce accuracy in vision and inertial-based systems.

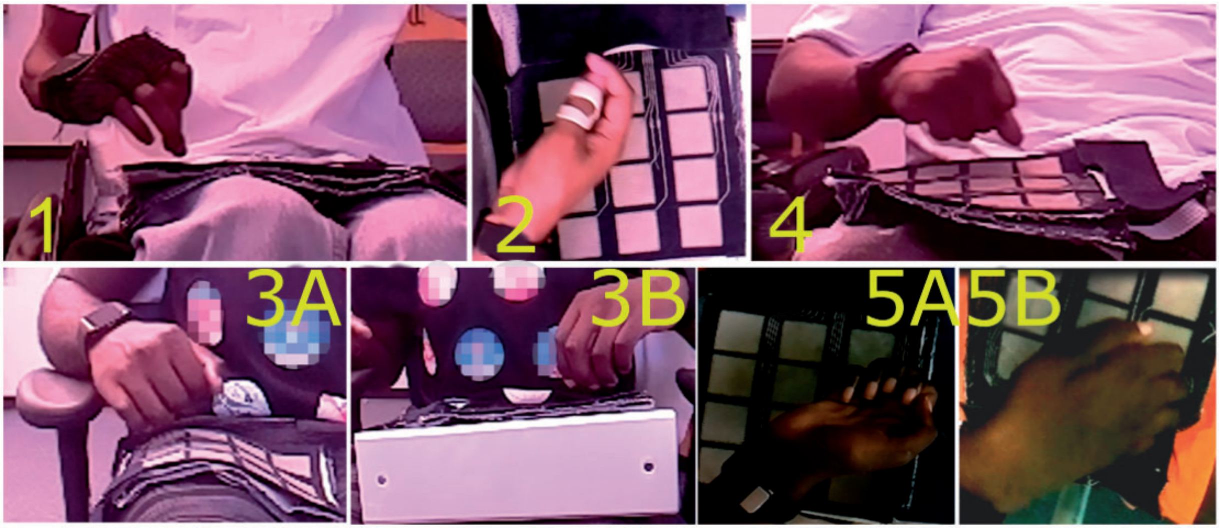

Figure 4. Hand position of the five subjects in the study. Each individual chose to use a unique hand position in performing gestures, demonstrating the need for personalization.

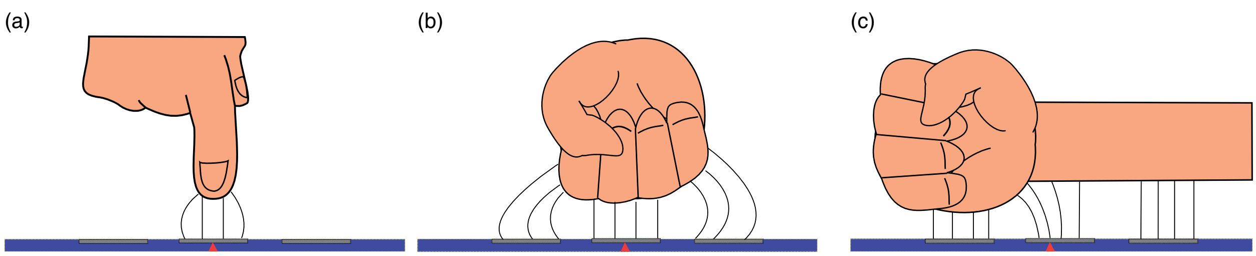

Figure 5. Demonstration of how the capacitance centroid calculation can be affected by various hand positions. The red triangle indicates the position that the centroid would be calculated in one-dimension above the array. The black lines are approximate capacitance based on distance to the body. Notice that the finger (a) is very localized, and must be closer to obtain the same amount of capacitance as the fist. The fist (b) has a large sum capacitance and the centroid of capacitance is centered roughly with the position of the fist. The arm (c) has a very large sum capacitance, but the centroid is shifted away from the fist due to the arm extending across the other sensor pads.

The effect on the CSA is demonstrated through the depiction of the position centroid calculation in Figure 5.

An artifact that is more specific to the CSA-based system is that the angle in which one approaches the CSA can affect the position calculation. Subject 4 has multiple incomplete spinal cord injuries, and consequently his mobility profile is more diverse. He is capable of using an upright platform walker, but his movements are typically slower and his shoulder movement is less pronounced. When he uses the CSA, his entire arm stretches across the array, which greatly spreads out the calculated centroid for position. This effect is demonstrated in Figure 5(c). Therefore, it was easier for him to have the array oriented toward him on an incline, shown in Figure 4(3B). Additionally, depending on the movement, he may choose to use the hand that is closer to the majority of motions so that there is not as much strain of reaching across the array.

These adaptations by the user allowed them to approach the CSA in a way that was comfortable and provided maximal accuracy given a template gesture set. This training phase is indicative of a typical motor-rehabilitation session with an occupational therapist as a person learns to use a new assistive device. However, assuming that a person will be able to adapt their gestures to the device is dangerous as many users may not have the ability to perform certain motions based on mobility constraints. Therefore, in order to perform per-person personalization without requiring the user to adapt to the system, we want to consider the inverse; a system which *adapts* to the user. To enable this, we consider adapting the gestures to fit each individual's own mobility profile through custom templating. This adaptation is introduced, and a potential solution is evaluated in "Adaptations for Personalization."

Insight 2: Explicit feedback in the form of visualization is important for training

Applying the importance of controlled feedback in motor learning and rehabilitation, a portion of the study was conducted to determine how a user's gestures may vary as a function of the type of feedback which they are receiving. As the user was initially learning the system and the EdgeWrite gesture set, instantaneous feedback was provided in the form of virtual reality visualization. This component was removed and replaced by verbal confirmation of correct gesture performance. The verbal confirmation was then removed and replaced by activation of home automation hardware. In the second trial, the user was instead prompted first with the verbal confirmation. We then covered the array so that they did not have localized visual feedback, and were only provided with verbal confirmation. While learning a new set of gestures, they were provided with the online feedback. The session ended with the home automation activation as feedback.

In all of these trials, the gestures that they were performing were evaluated for accuracy in real time against template gestures. The home-automation component provides motivation for the user to correctly perform each gesture as the system is intended to be an accessibility device which could help these individuals in the future. It is natural, then, for the method in which the user performs the gesture to change over time as they attempt to match the template to obtain a higher accuracy. The individual is *learning* the system based on the visual online feedback. Therefore, the online feedback through instantaneous positional data was removed once the user was trained on a gesture to prevent manipulating the particular user's form. The user was instead provided only with knowledge of results based on confirmation from the attendant, or activation of home automation hardware.

Analysis of gesture timing demonstrates an important factor in removing the instantaneous feedback. When the user is given the visual feedback they tend to try to trace the gesture specifically, which can lead to slower more diverse gestures. The gesture speed reduction is shown across four of the five subjects. The gesture length throughout the trial is demonstrated in Figure 6. Without visual feedback, the user tends to focus solely on their own hand in relative position to the CSA, which results in quicker more fluid motions.

To test this, we experimented with covering the CSA with a nonconductive material so that the user did not have the ability to locate the gesture to specific pads. This is shown in Figure 7. Removing the ability of the individual to see the CSA results in smoother gestures, but did result in slightly lower accuracy as subjects would move their hand outside the bounds of the array, causing the gesture to terminate early. The overall gesture accuracy without any visual location confirmation dropped approximately 7% compared to performing just without the virtual reality feedback.

In order to consider a particular gesture to be trained for a user, the motion should be consistent and fluid, which is produced only once the instantaneous feedback is removed. The VR feedback acts to demonstrate the gesture, and allow the user to properly plan and learn the routes, but is a crutch that needs to be removed for motor learning to properly occur.

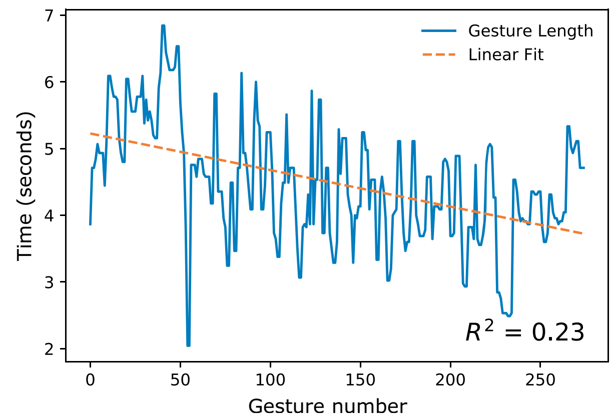

Figure 6. This figure demonstrates the length (in seconds) of each gesture for Subject 1's first trial. A linear fit line demonstrates a reduction of over a second per gesture throughout the trial.

Figure 7. This figure shows a portion of the trial where we cover the capacitor sensor array with a nonconductive material so that the motions can still be captured, but the user cannot see where their hand is with respect to the plates.

Personalized gesture recognition

In this section, we introduce an adaptation to the CSA recognition algorithms derived from our observations in the user study. Using personalized training data for gesture classification based on each user's own motions, we attempt to derive a representative gesture set from the user's own motions. Using a data-driven approach to generate these templates guarantees that the gestures fit within the user's own ability, as they are created from their own motions.

Gestures as input have become a familiar mode of interfacing with devices. Some argue that gestures are a more natural user interface while others consider that gestures, by their ephemeral nature, lead to inherent confusion when misclassification occurs.[29] A common thread among the field is that accuracy (reduction of both false-positive and false-negative classifications) and availability are important factors when considering gesture interfaces. Accuracy can be increased with sophisticated signal processing, but that can come at the expense of increased power, which can limit the availability of systems due to reduced battery life. A compromise exists in the use of personalization in the gesture recognition software. The CSA system used in this study uses DTW as a recognition algorithm. DTW is a vector-quantization classifier that calculates a Euclidean distance of time-warped positional data, and compares the relative distances against a set of template gestures in the recognition codebook. Personalization of the gesture set can be implemented through replacing the codebook with gestures that are indicative of those performed by the actual user. This personalization is important for gesture recognition; with more similarity between a candidate gesture and the template gestures comes either higher accuracy or a more dense set of gestures. Consistent user motions that are not reflected in the templates should be corrected. Figure 8 demonstrates this phenomenon as the largest proportion of a subject's motions is not captured correctly by the template gesture.

To perform this adaptation, we introduce two methods to replace the gesture recognition codebook. First, we enable the user to create their own gesture set through a distinct training session. Second, we consider beginning with a template set, and including the user's gesture data in the creation of user specific templates. Both adaptations are discussed in the following two subsections.

Targeted training session: The first adaptation considers a specific targeted "training" session. In this session, a user decides on a set of gestures which they want to include in the set. The user then performs a number of these gestures, and a representative set is chosen to be included in the codebook. This process is manual, requiring a reviewing procedure for selecting and curating gestures. We have created a toolkit that is usable by occupational and physical therapists to help a user create a set of gestures. Our implementation is depicted in Figure 9.

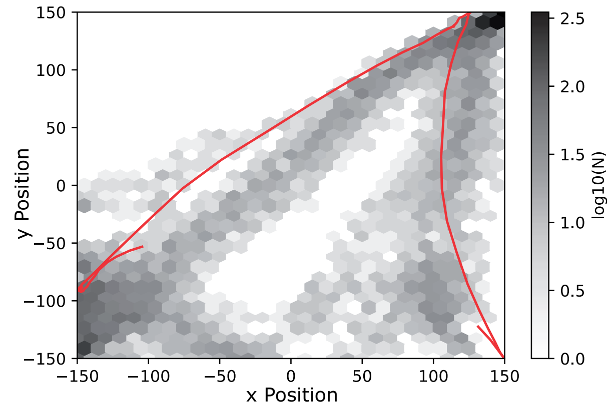

Figure 8. This picture demonstrates a heat map of a particular subject's gesture "A" compared against the template gesture "A," which is represented by the red line. The inconsistency along the left-hand side of the gesture represents a consistent error that reduces the relative accuracy between these gestures, and could potentially result in an incorrect classification.

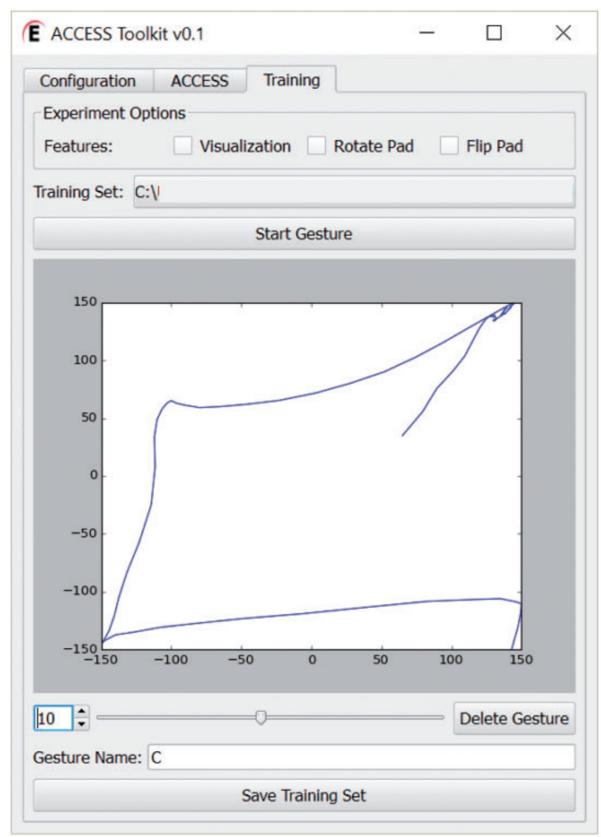

Figure 9. Training tab for the CSA system.

Incorporating in situ motions: As an alternative or extension to the training session, a template set of gestures can be slowly replaced with the user's actual motions. This can be done in a number of ways. For one, a user can provide periodic feedback about the correctness of a classified gesture, either through verbal or behavioral feedback mechanisms (e.g., If the user does not try to correct the home automation actions that were performed, or does correct in a specific manner). Another method is to create a profile of the average motions, which are classified as a particular gesture. Either of these methods have the additional advantage of allowing the system to evolve with the user over time. Enabling in situ adaptation is particularly useful for assistive applications where a user's mobility profile may change over time, whether through gaining additional motion through therapy or losing mobility through the progression of a disease or injury state.

To simulate the creation of a test set, we chose three gestures of each classification (i.e., three each of each "A "–"E" gestures) from the beginning of each user's first trial which had the smallest relative distance to the other gestures in the trial. These gestures should be similar to a representative set of gestures selected during a targeted training session. The gestures chosen for the codebook were removed from the evaluation set, and then the accuracy was re-evaluated with the new "personalized" gesture set. This method resulted in the results shown in Table 3.

From Table 3, we can draw a couple conclusions. First, the training accuracy, represented the highest accuracy increase when using a personalized gesture set. The gestures performed during this segment were often different than the rest of the set in both cadence and motion paths. After removing the instantaneous visual feedback from the user, their motions began to be more consistent, and the motions more typically followed the template set as the user properly "learned" each gesture. Second, Subject 3, who had struggled to use the system in the first trial, fundamentally changed the way he approached the system such that the personalized gesture set tailored to him from the training data of the first day no longer matched the motions he was performing. This suggests that changes in status that manifest in new motion profiles can greatly inhibit the consistent use of such a system over time. *This last conclusion points to the necessity of wearable assistive devices to continue to learn about the user and adapt its internal classification algorithms.*

Table 3. Accuracy of gesture classification when using a personalized set of gestures.

User	Training and evaluation	"Testing 1"	"Recall 1"	"Recall 2"
1	100% (+5.6%)	97% (+0%)	100%	89%
2	95.8% (+0.8%)	88% (−2%)	92.9%	95%
3	100% (+13.6%)	72% (+5%)	N/A	79%
4	100% (+5.8%)	91% (+1%)	96.6%	94%
5	100% (+7.5%)	95 (+3%)	98.0%	92%

In situ gesture personalization

As described above, the ability to adapt to previously classified motions to continually modify the template gestures can greatly extend the lifetime usability of assistive wearable gesture recognition. In this section, we propose and evaluate a method for calculating and inserting these personalized gestures into the template gesture set.

Figure 10 demonstrates an important factor in the creation of these personalized evaluation sets. The histogram shows that the relative distances can be an additional predictor toward the "correctness" of a given gesture. This knowledge enables the ability to select specific gestures with high correctness probabilities to be inserted into the template set without the need for explicit feedback from the user. However, these correctness values are probabilistic, and therefore the selection algorithm should provide an extra level of filtering to remove gestures which appear to be correct classifications.

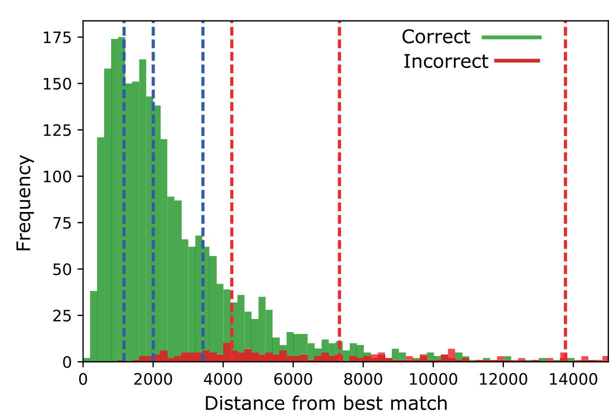

Figure 10. This histogram demonstrates the relative accuracy as opposed to the binary classification accuracy. Gestures are cast into bins based on the distance metric calculated by the dynamic time warping algorithm. Green bins are correctly classified gestures, and red are incorrectly classified gestures. The dotted lines are the 25th, 50th (median), and 75th percentile for each correct and incorrect. This figure demonstrates that knowing the relative distance can be useful in determining the correctness of a classified gesture.

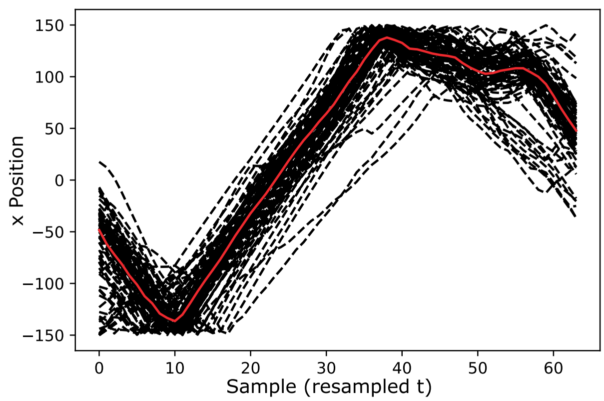

Figure 11. This figure demonstrates a resampling of the x-coordinates of a particular subject's "A" gestures from the first trial. Each black line is a single gesture performed by the subject. The red line is the median value at each point *i* in the time series. The median point at each sample is collated into a composite gesture, and thus creates the personalized gesture.

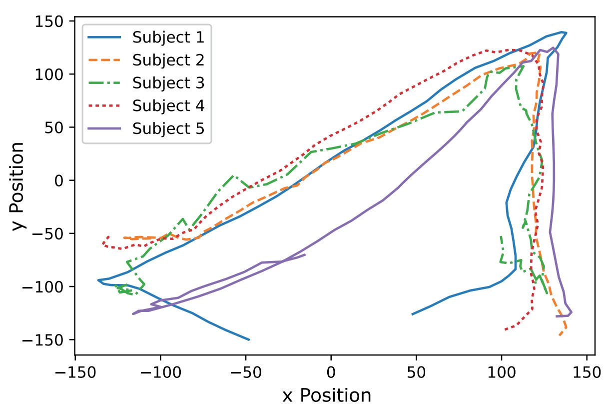

Figure 12. This figure demonstrates each of the five median 'A' gestures created by the subjects' gestures during the first trial. These are used to classify gestures from the second trial as an additional comparison point to static templates.

A median filter is a fairly simple approach to removing outliers and selecting the average data from a series. To use a median filter for this application, there are some modifications that must be made. First, gestures can have different lengths as discussed above in Figure 6. In order to select the median set of (x,y) positions in a time series, the inputs must be resampled to vectors of the same size. Further, gestures may vary in cadence (i.e., the relative speed of specific motions). This means that points in time along two gestures may not line up to enable proper use of the median filter. Therefore, the resampling method should not maintain time invariance, but should instead maintain the aspect and position data as best as possible. A similar method is discussed in the Wobbrock et al. $1 Recognizer paper.[30] This resampling method calculates the entire distance of the composite line segments, and selects evenly spaced points along the original path.

After resampling a set of gestures, the median filter then calculates the median × coordinate and median y coordinate at each point (t) in the time series. This is demonstrated in Figure 11 for the x-coordinates of Subject 1's "A" gestures. This procedure is done for each subject and each gesture to create a personalized gesture recognition codebook, which can be used for classifying the gesture set. The variability that exists between these gestures on a subject-by-subject basis can be seen in Figure 12.

To evaluate this gesture set, we compare the classification accuracy between the template gesture set and the personalized gesture set in Figure 13. The classification was performed only on Trial 2 gestures, while the personalized gestures were selected from only Trial 1 gestures. Using the personalized gesture set resulted in a reduction of 7% (three additional misclassifications) for the "B" gesture, and a gain of 11% (four additional correct classifications) in the "E" gesture. While this is a modest gain in accuracy overall, continuing to adapt

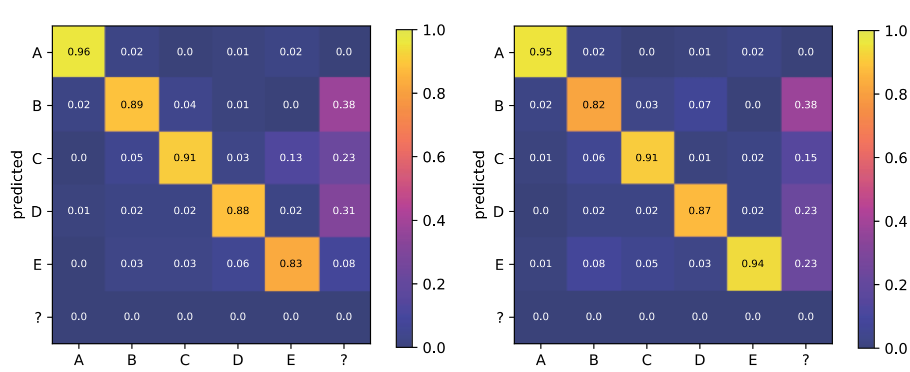

Figure 13. These two confusion matrices demonstrate the accuracy change when using the template gesture set (left) and the personalized gesture set (right) for all subjects.

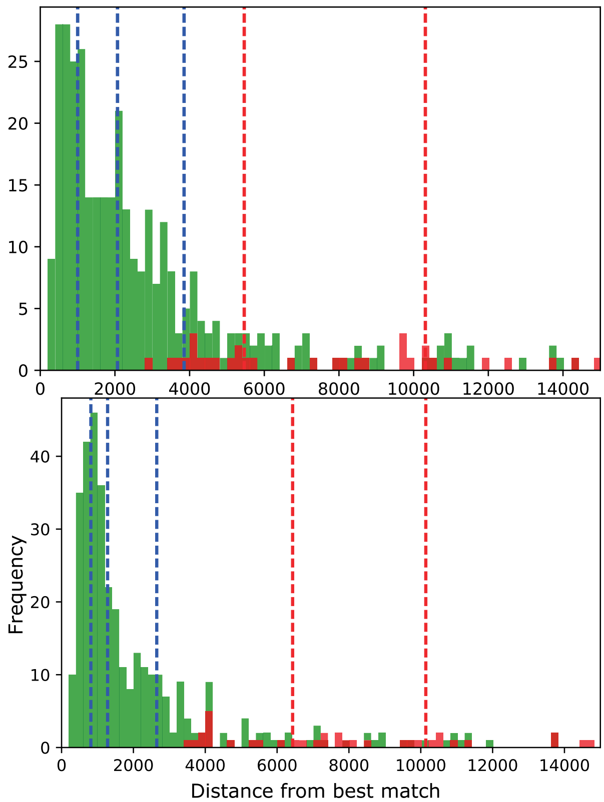

Figure 14. This figure demonstrates the relative distances between the template gesture set (top) and the personalized gesture set (bottom). The personalized gesture set has a much smaller relative distance for classification than the template gesture set.

to the user's motions should result in a higher accuracy over time. This can be shown by the relative error which can be calculated by the distance metric discussed above. Figure 14 demonstrates this through two histograms of the relative distances between candidate and codebook gestures for a personalized and a template set of gestures.

Conclusion

This paper evaluates the usability of CSAs as an accessibility device for persons with upper extremity mobility impairments. In verifying the accuracy of the system, we establish two insights into the development and training of a wearable accessibility device. First, personalization is important, both on the part of the user adapting to the system, as well as the system adapting to the user in a symbiotic feedback loop to create an accurate, responsive interface. Second, training users in accessibility devices can be improved through the control of knowledge of results. By modulating what feedback the user receives during training, the practitioner can motivate particular behaviors to allow user's to feel comfortable using the system. From the first insight, we proposed and evaluated two methods of creating a personalized gesture set through study of motions performed by people with motor disabilities. The first uses a specific targeted "training" session to generate static personalized gestures comprised of the individual's own motions, to ensure that the gesture set fits in their own mobility profile. The second considers continuous adaptation by selecting the average correctly classified gesture in a set to add to the codebook, and slowly replace the template set. This adaptation allows the gestures to evolve over time with the user's mobility of the gesture recognition algorithm through the use of the individuals' own movements in training. The insights and adaptations derived in this paper enable this textile accessibility system to be more available and more accurate to users, and create a more sustainable and reliable system for people to interact with their environment.

Declaration of conflicting interests

The author(s) declared following potential conflicts of interest with respect to the research, authorship, and/or publication of this article: NB, RR, and CP have a patent under submission for the technology. "System and Method for Proximity-Based Position, Movement and Gesture Detection Using Capacitive Sensor Array"—Patent Application number: 14/523,347.

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Guarantor

AN.

Contributorship

AN, RR, CP, and NB developed the sensor for the study. SMW was involved in gaining ethical approval, recruiting subjects, and developing the study. AN performed the data analysis and wrote the drafts of the manuscript. All authors reviewed and edited the manuscript, approving the final version.

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