2. Related Work

The spotting task of gesture recognition is much more challenging, since it is difficult to spot human motion events from number of sources. Another challenge is the system has to deal with the motion events to be spotted may only occur in a continuous data stream, while at the same time embedded into other, These movements are difficult to model due to their complexity and unpredictability. The study of gesture recognition has been continued over years and many approaches have been proposed till now. These approaches are categorized in two ways, first is gesture recognition, requiring external infrastructure and the second is gesture recognition focusing on wearable instrumentation. The first category is the vision-based motion recognition in this multiple cameras can be used for gesture recognition. The second category is started working recently and over the few period of time this has gained much attention[7]. This system which we are using in this paper is based on the second category also it is based on the previous work on capacitive sensing, gesture recognition systems and signal processing algorithms.

A. Capacitive sensing technology

Capacitive sensing technology is very popular in industrial, automotive and healthcare applications[13]. It has also been applied to positioning [15], humidity sensing[17], and tilt sensing[19]. This technology used to replace optical detection methods and mechanical designs for the applications like gesture detection and material analysis. The main advantage of the capacitive sensing over the other gesture detection approaches are that it can sense different kinds of materials such as skin, plastic, metal etc. it is contactless and wear free, it also has the ability to sense large distance with small sensor sizes, it has low cost and low power solution. Capacitors as proximity sensors have applications to robotics, industrial monitoring and healthcare systems[13]. We present an end-to-end gesture recognition system including a 2D array and results from 2D tracking and gesture classification using a wearable capacitor array[1]. Products like Microchip's GestIC [24] allow for 3D gesture tracking using rigid capacitor arrays. The non-rigidness property of our sensors allows for sewing them into clothing and into the environment such as bed sheets, pillow covers, and wheelchair pads. Additionally the use of capacitive sensors (CSA) allows to work collaboratively to reduce environmental noise and capture motion attributes like speed and direction of motion[1].

B. Gesture recognition system

Gesture recognition system interprets the human motion by computing device mathematically. Gesture recognition with facial recognition, voice recognition, lip movement and eye tracking are the components of which developers refer as perpetual user interface (PUI). The goal of PUI is to enhance the efficiency and ease the use of the underlying logical design of a stored program[1]. Most of the time the gestures are used for input commands. Recognizing gestures as input allows computers to be more accessible for the physically-impaired and makes interaction more natural in virtual environment. Hand and body gestures can be amplified by a controller containing accelerometers and gyroscopes to sense tilting, rotation and acceleration of movement or the computing device can be outfitted with a camera so that software in the device can recognize and interpret specific gestures. A wave of the hand, for instance, might terminate the program. The increase in adoption of home automation technologies has spawned the new platforms for control based on gestures. for instance, allow environmental control without physical contact with a controlling device. Home automation techniques have been adapted to enable users with limited mobility to have greater autonomy over environmental control. These platforms include voice-activated systems [17], head-tracking [18], EOG based eye-tracking and inertial sensors [19]. In this signal processing algorithm adapts to the user and changes in the configuration of the sensors with minimal training. Additionally, unlike systems like cameras, this system is effortless and can be built into clothing and embedded into the environment such as pillows and bed sheets.

C. Signal Processing for Gesture Recognition

There is a large body of work on applying signal processing techniques to gesture recognition. Learning techniques such as Hidden Markov Models [20], decision trees [21], and Bayesian inference [22] have been applied to converting data from sensors such as accelerometers to movement activities and gestures. Learning approaches such as HMMs have also been applied to applications such as handwriting recognition [23]. We adapt two classification approaches, Hidden Markov Models and Dynamic Time Warping to our system to convert data from a capacitive sensor array into alphanumeric gestures.

3. Textile Capacitor Sensor Array For Gesture Recognition

The gesture recognition sensor consists of textile based electrodes which built into clothing or into the environment. Out targeted users often lack of sensation in hands for them it is critical for regulating the contact, the repeated contact can be damaging to the skin to various degrees. Depending on the surface underlying. We also can create a touch-based swipe interface, in this the characters can be drawn directly on the fabric surface. The problem with this interface is that this can be develop skin friction injuries.

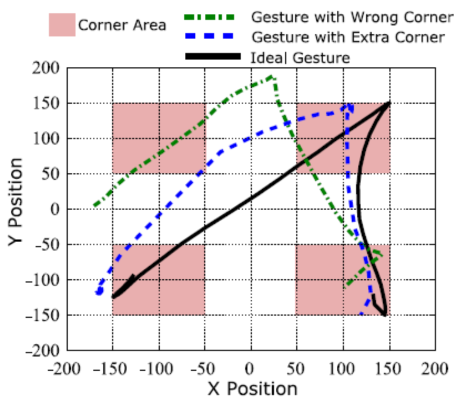


Figure 2: The gestures evaluated in this paper are based on EdgeWrite [26] gestures, for which users are taught to envision motions though corner areas in specific orders to encourage distinct gestures. Even so, robust classification is

required. This figure depicts two situations, from three gestures within our dataset, where a state machine approach does not suffice for classification.

As fig 2. Shows the user do not always perform the exact gestures as required. Therefore we have instructed the individuals using EdgeWrite gestures set to perform distinct gestures, in order to create a robust interface so that users does not require to direct full visual attention to the interface, but still we have need the more accurate and sophisticated gesture recognition algorithm than EdgeWrite. The figure shows two situations. In this EdgeWrite state machine approach will fail due to omission of states or adding extra states. Then we presents the touch less interface, where gestures can freely performed in the proximity of the sensor. Because of this we can perform gestures with frictionless and touch less. The signals detected at the proximity have lower power and higher variance than the touch based interfaces. In the touch interface the signals are easily thresholded to create binary detection in each point of the array. Where as in touch less interfaces binary thresholding is not reliable[1]. Capacitive sensors work on the principle of change in Capacitance the electric fields between the plates of capacitor makes them highly versatile. Accelerometers and gyroscopes measure movement of the body to which they are attached. capacitive sensors can sense movement of remote bodies.

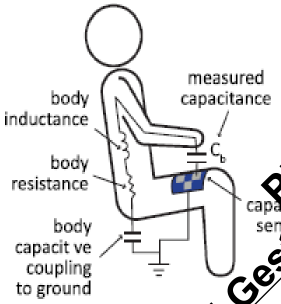


Figure 3 (a)

Figure 3 (b)

Figure 3: (a) Equivalent electrical circuit when a capacitive plate is placed on the leg and the user performs gestures using his hand. The body is capacitively coupled to the sensor ground using a sensor ground plane
Fig 3(b) Longitudinal cross sectional view of the sensor.

Fig 3(a) illustrates the principle using an example where an array of capacitive plates is worn by a user and gestures are performed by moving the hand in the vicinity of the array without touch. The body of the patient is capacitively coupled to the ground of the sensor system. When the hand is moved close to the capacitor plates, the capacitance Cb increases. Inversely, the value of capacitance Cb can be used to localize the hand with respect to the plates. The range of our capacitive plates is sufficient to prevent accidental touch and skin abrasion and can be adapted as the range is variable with plate size and shape. In Fig 3(b) The longitudinal cross-section of our designed sensor is illustrated The top layer is a network of capacitive sensor plates connected via conductive threads. An AC shield plane minimizes parasitic capacitance and noise coupling. The ground plane capacitively couples the human body to the ground of the sensor and provides a common reference for the capacitance measurements.

4. Classification Algorithms for Gesture

There are many algorithms for gesture recognition. For instance, Optical Character Recognition (OCR) algorithms This is adapted for recognizing characters from the tracked hand positions. OCR, however views the set of positions as an unordered set and does not leverage the temporal variations of the tracked positions and direction of motion. Using both the temporal variation in the data and the direction of motion is critical in our application where the same gesture can be performed very differently over time. In order to take advantage of the temporal ordering of the data, we chose to evaluate our system by adapting two techniques: Hidden Markov Models and Dynamic Time Warping. HMM is a statistical learning technique that performs well when there is large variations in the way the gestures are performed but requires substantial training and DTW is a time series based technique which requires minimal training. These two algorithms help us evaluate trade-offs in training, efficiency, and accuracy of gesture recognition across multiple subjects.

A. Hidden Markove Model

The Hidden Markove Models are used in almost all current speech recognition systems, in most of the applications such as computational molecular biology, in data compression and in other areas of Artificial Intelligence. A Hidden Markov Model is defined as a stochastic finite state machine. The algorithm is illustrated in Algorithm 1 Formally, it is defined by 5-tuple $\Omega=(S,\Sigma,\Pi,\delta,\lambda)$ where S represents a set of hidden states that are not directly observable. Transitions between the states is denoted by a transition probability matrix, δ. Π is the set of initial probabilities corresponding to the states in S. Every state has a set of possible emissions Σ and continuous probabilities λ for these emissions. The emissions can be observed by giving some information about the most similar underlying hidden state sequence which led to a particular sequence of observations. The HMM model assumes that the underlying physical process is Markovian, that means any prediction of future behavior can be optimally calculated by knowing the present state without any history. We map such a Hidden Markov Model to our problem of decoding a gesture based on a time series of hand position values. This definition of states constraints the set of gestures for which the Markovian assumption is valid. Our evaluation, however, demonstrates that this state definition works well across a large set of gestures.

Algorithm1. HMM Feed Forword(O, Φ, Σ, π, δ, λ, k)

Input: Observations (O):{$(x_1,y_1),\ldots,(x_n, y_n)$} for the gesture, Hidden states (S): {1,….k}, Initial Probabilities: {$\pi_1,\ldots, \pi_k$}, Transition Probabilities: $\delta(i, j),(1 \le i , j \le k)$, Emission probability distribution: $\lambda_1,\ldots\lambda_k$ (Gaussian (μ_k,σ)) for every state k ϵ [1,…len(S)]

Output: p (Model Probability given the Observations)

for i: =1 **to** len(O) **do**
for k: =1 **to** len(S) **do**
Emission = $(1/(\mathrm{distance}((x_i,y_i), \mu_k)/\sigma)^2)+3$
for j: =1 **to** len(S) **do**
p(i ,k) = p(i ,k)+p(i – 1, j) x Emission
end for
end for
end for
return Σ_k p(|O| - 1, k)
Asymptotic Running time complexity: $O(|O| \times k^2)$

The transition probability matrix, δ is determined during a training phase when the subject performs a set of gestures. While calculating the probability of transitions between states, we make the following key adaptation to fit our problem domain. We have found that if the sampling frequency of our sensors is large compared to the transition rate, the transition probability matrix begins to resemble an identity matrix, and the importance of transitions between states is diminished.

The emission probabilities λ is calculated according Gaussian function. Each state is assigned a center position. The distance (D) from the estimated position and the center is used as the input for the Gaussian. The Gaussian width (σω) is approximately 1/3 of the center-to-center plate distance. This width is determined and used throughout the experiments. For computational efficiency, we use the following approximation ((D/ σω) + 3)-1 for the Gaussian. Applying the above modifications to the HMM we generate a model per gesture. the gesture to be classified is passed through each of these models to create a vector of posterior probabilities relating to each underlying model, and the model with the highest probability is selected as the classification for the gesture.

B. Dynamic Time Warping

Hidden Markov model builds a statistical model for the gestures. It also accurate in decoding gestures which have variations. This model must trained on a large set of gestures. The Dynamic Time Warping is alternative to a statistical model. The DTW handles variations in time and position which allows a dynamic variation in the temporal pace of gesture. Gesture are compared to a codebook of reference gestures by finding the best-case dynamic temporal distortion to compare two gestures. Dynamic temporal distortion contrasts an approach using a uniform time scaling that assumes the entire gesture is performed with a single speed factor. This avoids requiring a reference gesture for every possible timing variation. Variations in the positional path are handled by providing a representative set of gesture variations in the codebook. This set is sufficient enough to classify gestures using unsupervised clustering algorithms such as a single nearest neighbor or a k-nearest neighbor. An optimal choice of dynamic time warping and minimum error is based on a euclidean distance metric.

Algorithm2.DynamicTime Warping(*O*,*M*)

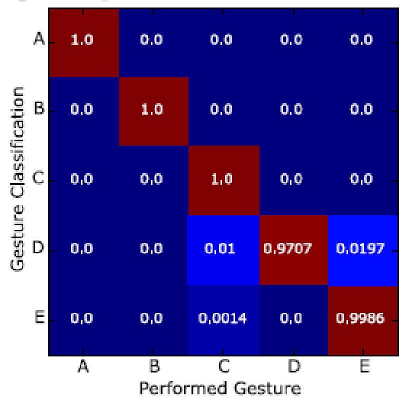
Input: *O* =[$(x_1 ,y_1),\ldots,(x_n , y_n)$] (positions for the gesture)
M = [$(x'_1 , y'_1),\ldots,(x'_n , y'_n)$] (model positions for the gesture)
Output: d (Warped Distance),
d(0,0) = distance(M(1), *O*(1))
for i:=1 **to** len(*O*) **do**
d(i ,1) = d(i -1, 1)+ distance(*M*(1), *O*(i))
end for
for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

5. System Evolution

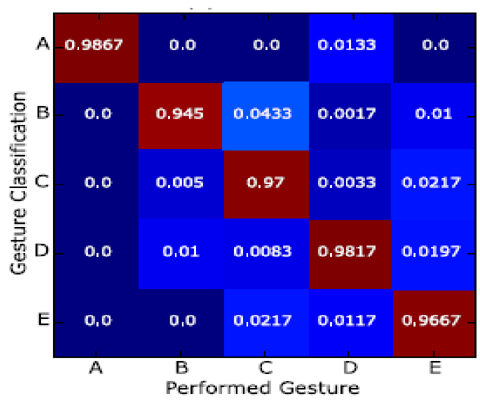
The goal of this system is to provide highly accurate gesture recognition so that users can adopts to changes in the position and orientation of the sensors. The sensor array moves and rotate according to the user hand. The HMM and DTW model would ideally need to be retrained on the gestures for every rotation, to overcome this problem a system is designed that augments the capacitive sensor array with a wrist worn accelerometer band, this band could be replaced by smart watch.

5.1 Experimental Setup

We tested this system on five subjects, who has C6 spinal cord injury. For each session subject were asked to perform the five gestures, during the experiment ten of each type of gesture at different rotation of degrees of the sensor array, Hence a total 150 gestures performed per subject.



(a) DTW



(b) HMM

Figure 4: (a) Confusion matrix illustrating the accuracy of recognizing the five gestures performed by all the subjects when our system used Dynamic Time Warping. (b) Confusion matrix illustrating the accuracy of recognizing the gestures performed by the subjects when our system used Hidden Markov Model. For both figures, the confusion matrix is calculated using 150 _ 5 = 750 gestures. Our system has an average accuracy of 99 and 97 percent for the DTW and HMM models respectively.

The figure 4 illustrate the classification of accuracy of gesture recognition algorithm. The figure generated using data from all gestures performed by five subjects when sensor array rotated different degrees with respect to hand. The average accuracy is 99 and 97 percent of DTW and HMM respectively. If there is a large variation in the way of gestures performed then HMM model would perform best while the DTW would perform poorly.

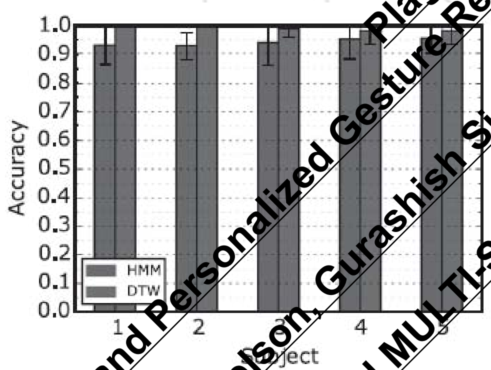


Figure 5: Accuracy per subject for five gestures when the classification algorithm uses a DTW model and an HMM classification.

The figure 5 illustrates the accuracy of the DTW and HMM based gesture recognition per subject. The height bar shows the accuracy across five gestures while the error bar shows the standard deviation in the accuracy across gestures per subject. The focus of this experiment on the subjects who has C6 spinal cord injury. The subject perform some set of gestures, and it shows that the accuracy of DTW algorithm on the gestures is 99 percent , Hence we can say that this system works very well even though the subject use limited mobility.

6. Conclusion

In this paper we proposed a system which uses the textile capacitive sensor arrays to recognize gestures for the users who are physically disable and unable to do their routine, this system can provide gesture recognition with limited mobility. The textile sensors are flexible and can built into clothing or daily use items such as pillow covers, bed sheets, wheelchair pads etc. An adaptive and personalized signal processing system can convert capacitance data from sensor array to alphanumeric gestures. The gestures can use then to control the appliances in the home. By using the wrist-worn accelerometer and the sensor array, the gesture recognition system correct the rotation of the sensor array with the hand with minimal intervention. This system has evaluated by using the HMM and DTW classification. The DTW is more computationally efficient option.

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