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Gesture Recognition via Flexible Capacitive Touch Electrodes

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***Abstract*— A novel wearable device for gesture recognition was developed and tested on five subjects. The low-cost, wireless wearable device was engineered with a set of seven flexible capacitive touch electrodes sewn into an armband to be worn on the forearm between the wrist and elbow. These capacitive touch electrodes were interfaced with a microcontroller and bluetooth transceiver for measurement and transmission. As different gestures are made, flexing muscles beneath the skin affect the capacitance measured on these seven electrodes. A set of 32 gestures were tested including the 16 grasps in the Cutkosky Grasp Taxonomy and 16 basic finger and wrist motions. Several classification algorithms were tested on this data. Using a Random Forest (RF) algorithm to classify the training data, an average gesture recognition accuracy of $95.6 \pm 0.06\%$ was achieved across all five subjects individually.**

I. Introduction

Exoskeletons and wearable robotics are emerging as a technology capable of enhancing the lives of the injured and elderly. They offer an attractive method of providing mobility assistance, stroke rehabilitation, and general physical therapy. While physical actuation has improved over recent years, there is still significant room for growth in systems for recognizing user intent and, specifically for this work, gesture and motion recognition [1], [2], [3].

For wide adoption, gesture recognition systems must be robust, low cost, accurate, easy to implement, and comfortable enough for daily wear. The current landscape for gesture recognition has several competing technologies attempting to fill this niche including surface electromyography (sEMG), force myography (FMG), and electrical impedance tomography (EIT). All of these technologies have some limitations within these metrics.

sEMG uses small electrodes to monitor the electrical signal of muscle neurons which control the muscles. While this is the clinical gold standard, the technology faces many challenges for widespread use outside the lab. Electrode pads are expensive, and obtaining clean signals requires significant preparation of skin and very precise placement. Even under ideal scenarios, significant signal processing is required. sEMG also suffers signal drift over course of the day, picks up environmental noise from electronics as well as neighboring muscle groups, and sweat can alter electrical signals [4], [5], [6].

FMG measures radial pressure of muscles as they contract and has been used with machine learning algorithms to achieve promising results in recent years. However, it is dependent on many as 32 discrete sensors being placed over thickest portion of forearm. This has several drawbacks including cost, the requirement of sensors to be worn directly against users' skin, and the potential for model accuracy to be diminished as sensors slip to different positions during normal motion [6], [7].

EIT has also seen some use in gesture recognition. In this context a bracelet carrying an array of electrodes is worn on the arm and a signal is sent out by one of the electrodes. The other electrodes read the signal and compare it to the input to determine impedance. While this method can be highly accurate, the authors indicate that it is highly dependent on placing sensor band at a specific location on the arm and requires direct skin contact [8].

This work presents a novel application of capacitive touch (CT) as an alternative method to sense recognize and classify human motion. The design we focus on uses continuous (versus many discrete) electrodes wrapped around the circumference of the arm to spatially integrate signals from a large number of muscles. The wristband format used is easy to don and comfortable enough for long term wear. Because CT measures proximity rather than direct pressure it also has the potential to be worn over clothing or bandages.

The primary contribution of this work is an exploration of CT using these circumferential electrodes for gesture recognition. To accomplish this, an armband was developed and experiments were conducted to explore accuracy of the system in recognizing a variety of grasps and individual finger and wrist motions. Data collected from subjects was processed using several common and well documented machine learning models.

II. Principle of Operation

Capacitive touch is a mature technology that has been used in a wide array of touch interfaces and proximity sensing devices. It is robust, low cost, and non-invasive, but the goal of this work was to determine both comfort and accuracy for gesture recognition.

An excellent review detailing taxonomy of capacitive sensing and various methods used to interface humans with machines via CT was compiled by Grosse-Puppendahl et. al. in 2017 [9]. Capacitance in its most basic form is a measure of energy stored in an electric field between a positive and negative electrode. This is described by the equation:

$$C = \varepsilon \frac{A}{d} \tag{1}$$

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In this equation ε represents the dielectric constant of the material separating the electrodes of overlap area A and d is the distance between the electrodes. Capacitance changes proportionally to ε and A, and inversely proportional to d. CT technologies measure how capacitance changes as a function of the human subject interacting with the electrodes, but can be complex since all of these variables can be changing at once.

Early investigations into CT as a means of gesture recognition focused on the use of a dual electrode active CT architecture (Fig. 1). This approach is similar to EIT in that it excites an electrode attached to the body and captures data from ground electrodes elsewhere on the body. Changes in capacitance were a function of both changes in distance between electrodes, and changes in dielectric value of the human body due to muscle activity [10], [9], [11]. While these methods can be very accurate, they are very sensitive to the position of the sensors, can be prone to environmental noise, and have a relatively high computational overhead.

In more recent research, a simpler single electrode architecture was adopted (Fig. 1B) in which the human body was treated as negative electrode, and capacitance changed as a function of distance between body and positive electrode. Zheng et al looked at controlling prosthetics with many pads placed directly over specific muscle groups; they achieved good results, but pads had to be mounted on a rigid surface and required placement over specific muscles of interest [12].

Other uses of CT to classify gestures or motion include the use of a positively charged ring on one finger to measure changes in capacitance caused by motion of neighboring fingers [13]. These results showed good accuracy but limited utility to finger-based gestures as they could only determine relative position of neighboring fingers. Baldwin et al used an electrode worn on one leg to count strides and determine distance between legs [14]. Capacitance was changed by the proximity of the neighboring leg. While effective for these purposes the requirement of measuring an external limb prevented shielding electrodes from external signals, and detailed information about muscle use or joint positions was not available [14].

This paper proposes a simple and low-cost approach to using CT for classifying gestures. In order to move or make gestures, many muscles must be contracted or relaxed in concert. The capacitance measured by a flexible electrode wrapped around the circumference of a limb will therefore change as the total amount of skin at a given distance from the electrode changes with each grasp (Fig. 2). The combination of muscles contracting and relaxing should produce a specific capacitive signature for each individual gesture. The hypothesis for this work is that the combined data from several electrodes wrapped around the limb will allow for accurate gesture recognition. Wrapping the sensors entirely around the limb should mitigate the effects of motion artifacts and eliminate need to place sensors precisely over individual muscle groups. Machine learning will be used to help classify unique capacitive signatures as different grasps. Given the physical simplicity of the approach as well as computational simplicity, this technique should allow for gesture recognition at a far lower cost in terms of parts and computational power than existing technologies.

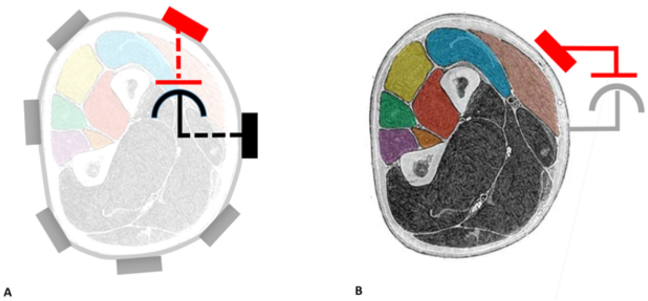


Fig. 1: Previous approaches using CT for gesture recognition. A) Dual electrode methods use the human body as a variable dielectric. B) Single electrode methods treat the human as a negative electrode and measure change in capacitance as a function of skin proximity to the positive electrode. Arm cross-sections adapted from [15].

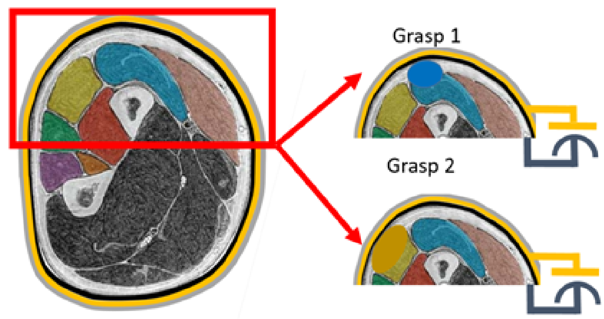


Fig. 2: The proposed electrode architecture encircles the entire arm. As a result it can spatially integrate the activity of multiple muscles at the same time, and generates a change in capacitance as a function of their combined contraction and relaxation. Two generic grasps are illustrated. In Grasp 1, the top muscle shown in blue is contracted and the left muscle shown in yellow relaxes. In Grasp 2 the top blue muscle relaxes, and the left yellow muscle contracts. Because this changes the distance between the skin and sensor strap, the two grasps result in different capacitive 'profiles'. Arm cross-section adapted from [15].

III. Materials and Methods

A wearable armband (Fig. 3) was constructed to assess the accuracy of CT sensing in a series of grasping experiments described here. It should be noted that the armband was designed to be placed only on the forearm of each user with the goal of classifying grasps and gestures through muscle activation in the forearm only.

A. Armband

The electrodes making up the positive electrodes of the capacitive sensor need to be conductive, flexible enough to

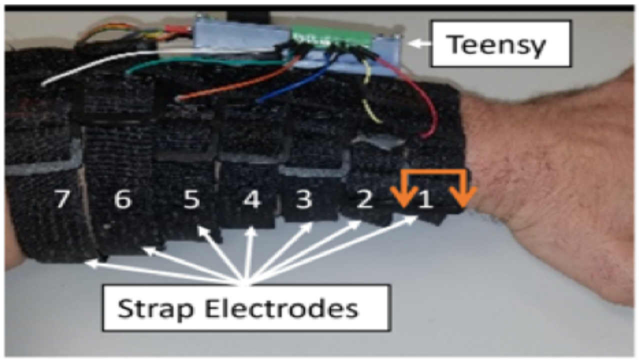


Fig. 3: The armband includes 7 capacitive touch electrode straps connected to a Teensy 3.2 and Bluetooth LTE radio. The armband is designed to fit over the subject's forearm and strap 1 is aligned with the knob of ulna bone on wrist to provide an anatomical landmark.

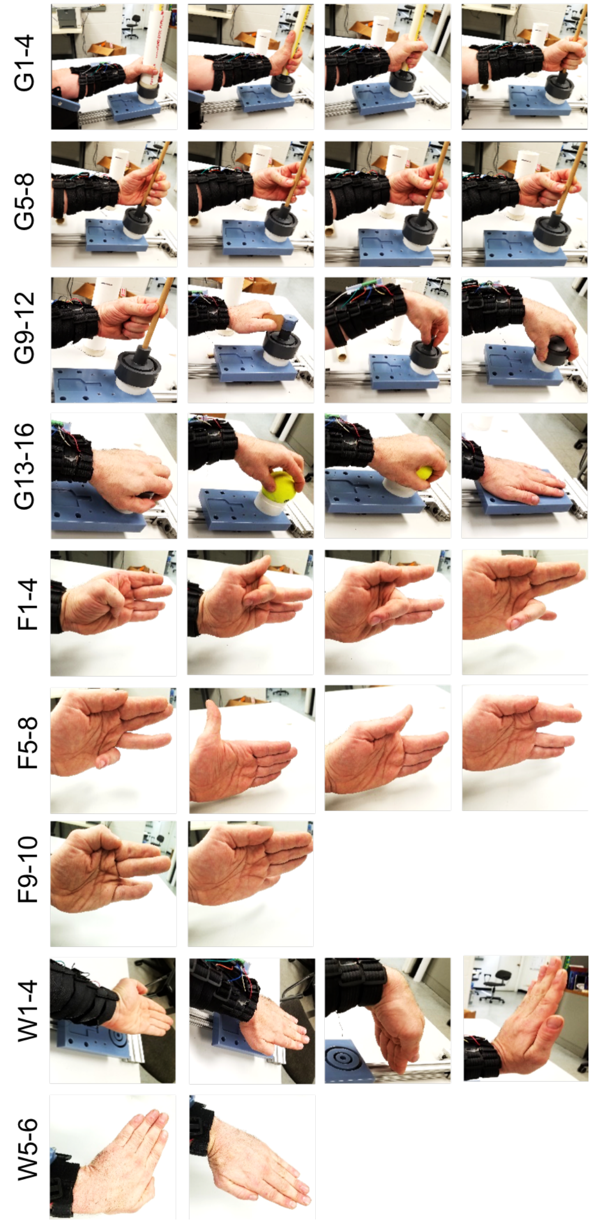


Fig. 4: Grasps G1-G16 were selected from CTG [16]; F1-F10 represent individual finger motions; W1-W6 represent wrist motions.

wrap around the arm, and adaptable and comfortable for human subjects of varying sizes. While several approaches were tested including conductive fabric and conductive elastomers, the simplest and most robust approach used copper tape. To allow for adjustment of straps to fit various human subjects, flexible electrodes were constructed by applying 6.3 mm wide copper tape to 19 mm wide snag-free Velcro tape that allowed each electrode to be tightened and fixed into place. The copper electrodes were sandwiched on the opposite side by nylon straps that were sewed to the velcro and used to create an additional dielectric barrier between the electrode and the human subject.

Seven of these electrodes were arrayed by sewing them to a piece of fabric that was used to adhere the on-board electronics. Spacing between electrodes was designed to be approximately equal at 22 mm apart. A Teensy 3.2 microcontroller board was selected due to its low energy consumption, 16-bit ADC resolution, and the presence of 12 integrated pins capable of capacitive measurement via the dual oscillator method. In this armband prototype, wires were soldered to the copper straps and connected to a header on a custom printed circuit board that also included the Teensy. In order to track arm angle for future work, a BNO055 IMU was also connected to the microcontroller. To allow for wireless communication between the armband and a computer (or phone), an HC-05 Bluetooth module was attached and used as a serial connection.

A companion application was built in Labview to collect data from the armband in real time at 20 Hz. This application also indicated the gesture that a subject should perform and enabled the authors to manually indicate when grasp events had occurred and ended using a button for labelling purposes.

B. Experiment

For initial proof of concept testing, five volunteers containing three men and two women were recruited to test the ability of CT to distinguish between 32 selected gestures (Fig. 4). 16 of these gestures were made up of grasps in the Cutkosky Grasp Taxonomy (CGT) [16]. This set was selected because it contains most grasps used in daily life and is relevant to both robotic grasps and physical therapy. An additional 16 motions were selected as representative of the typical range of motion for the hand and wrist. These motions included: flexion and extension of wrist, ulnar and radial deviation of wrist, supination and pronation of the hand, and individual flexion and hyperextension of each finger.

The sensor system was placed on a subject's arm, and the lowest strap was aligned to lie just behind the head of ulna to provide a constant anatomical landmark (Fig. 3). Buckles for the velcro straps were aligned with the radius bone on the inner arm. Subjects were then seated at a desk

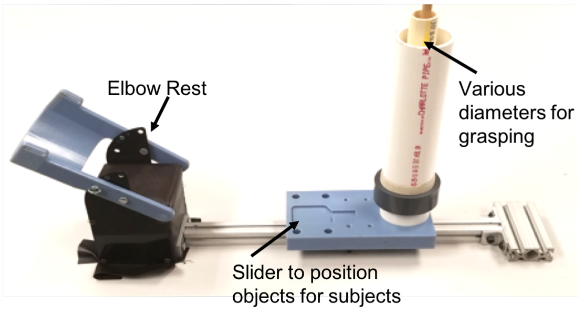


Fig. 5: Test rig used for consistent grasps between subjects.

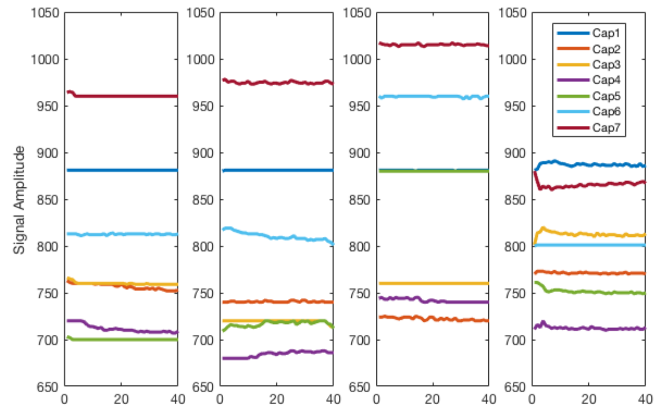


Fig. 6: Raw data from selected grasps taken from Subject 1.

and placed their arms in a rig equipped with an elbow rest to help the subject maintain position, and sliding stage to allow the various objects grasped in experiment to be moved to a comfortable distance from subject (Fig. 5).

When cued from the software, subjects would grasp an object or make the requested hand motion, press button to indicate their hand was in position, hold the position for 3-5 seconds, release button to indicate they were done performing gesture, and return their hand to a neutral position. For each grasp or gesture in Fig. 4, five repetitions were obtained giving 300-500 discrete samples. This experiment was performed once on each subject.

C. Analysis

Saved data was processed offline using Anaconda Python 3.6 with the scikit-learn library. A sample of the raw data collected for several gestures can be see in (Fig 6). Since the nominal capacitance for each electrode is different, the capacitance data was normalized to values between -1 and 1 and different machine learning algorithms were applied.

The goal of machine learning is to develop models relating the gestures (categories) to features (individual capacitive readings from the strap electrodes). Because the specific gestures being made were known through manual labeling, a selection of supervised machine learning algorithms detailed below were used. The particular features of these experiments important to consider when selecting algorithms are the large number of categories, likely nonlinearity of the capacitance data, and practicality toward a future embedded classification solution.

Linear Discriminant Analysis (LDA) is good at categorization problems with linear data. It also has a very low overhead which may make it suitable for embedded systems. LDA implicitly assumes a Gaussian density to each category, and that all categories share the same co-variance matrix. The sample data provided to the algorithm is used to find a line which can split between categories so as to maximize the ratio of between class variance vs out of class variance [17]. While effective for systems which are linear separable, it performs poorly on nonlinear data. For LDA, the default scikit-learn settings were used.

Under the assumption that data may not be linear, the Support Vector Machine (SVM) algorithm with a radial basis function (RBF) kernel was also tested. SVM casts data onto a hyper-plane using only the training points which are closest to decision boundaries and attempts to maximize the center distance between categories. The points closest to, or on, the boundaries are known as support vectors and the space between is the margin. Support vectors from each class are maximized to increase the margin to its largest possible size [17]. Because it is not constrained to linear relationships, it can find relationships that would be missed by LDA and has been used in a number of gesture recognition papers [6], [18]. The drawback of SVM is that it has a high processor overhead, which makes it less suitable for embedded systems. For SVM the commonly accepted default values of a C value equal to number of sensors and a γ of $1/C$ were used in testing.

The K-nearest neighbor (KNN) algorithm was utilized to determine whether cluster based methods would produce a better model versus linear or hyper-plane separations. KNN works by finding the mode value for each individual class based on finding nearest neighbors of each point in a training set. It works well when there are a reasonably small number of features and its models are easy to update over time with new information [17]. However, because it holds all data in direct memory, it can be very computationally expensive. The default setting of five nearest neighbors was used for this paper.

In order to investigate relative importance of each electrode feature, a Random Forest (RF) algorithm was employed. RF is an ensemble method which combines bagging and random feature selection. It operates by growing many decision trees in parallel. Each tree is built on a random selection of observations created through bootstrap sampling of the data and at each node the tree is split using a random selection of features with the goal of maximizing similarity of categories within the resulting subsets of data. This is repeated until a stopping condition is reached. A prediction phase is then entered where the same test data is presented to each tree. At each end leaf node of the tree, the most common category in the node is calculated. The predictions of all trees are then combined via a voting algorithm to provide a final selection model [19]. Advantages of the RF algorithms include the fact that they work for both classification and regression problems, have fairly low processor overhead, and that the analysis of many feature combinations in parallel allows for determination of relative importance of individual features. A downside is that RF has difficulty integrating new data, but researchers are currently investigating methods to overcome that limitation [20]. An ensemble of 250 trees was used in this paper's analysis.

When models trained on a given set of data are exposed to real world data they were not trained on, out-of-sample errors may occur. The 10-fold validation method is a common way of validating machine learning models against 'unknown' data.[21]. In 10-fold models, all samples from a single class are combined and then randomly shuffled. In this case, all data from the five iterations of a single grasp or gesture for each subject were combined before splitting into ten stratified samples. Stratified means that within each sample, the number of members in a given class is proportional to the overall data set. For each iteration, 9 of the stratified samples are used to teach a machine learning model, and the 10th is used to test the model. This is then repeated for 9 more iterations until each subset has been used once as a test model. The mean of prediction accuracy and variance are calculated. These values represent the expected performance of the algorithm on real world data.

Each of these algorithms was applied to the collected data for each subject. To test intra-subject accuracy grouped fold analysis was applied. In grouped fold analysis, one subject is held out to test models formed using the data from remaining subjects.

IV. Results and Discussion

A. Prediction accuracy of different algorithms

The average accuracy versus algorithm for the 10-fold validation tests are shown in Fig. 7 . For all subjects tested, RF proved the most accurate algorithm, and the KNN model came in as a very close second. Given the large number of categories, this is not a surprise. As mentioned previously, instead of looking at boundaries between categories or distances between them, the randomness of RF does a good job with data that does not have clear linear or polynomial boundaries.

B. Individual subject accuracies

For purposes of demonstrating predictive capabilities, confusion matrices were built using the RF model. In confusion matrices, the x-axis represents the predicted class, and y-axis represents the actual class. The diagonal down the center represents correct predictions, and the intersecting squares give data about what proportion of incorrect predictions fall into each class. The model generated by Random Forest was then used to build a confusion matrix for each subject showing which gestures the model had difficulty in predicting. These matrices can be seen in Fig. 8. The only one to show any significant error was Subject 4, whose plot has been expanded for easier visualization.

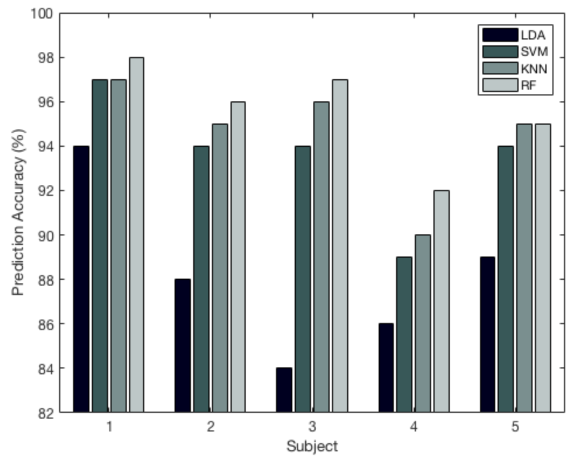
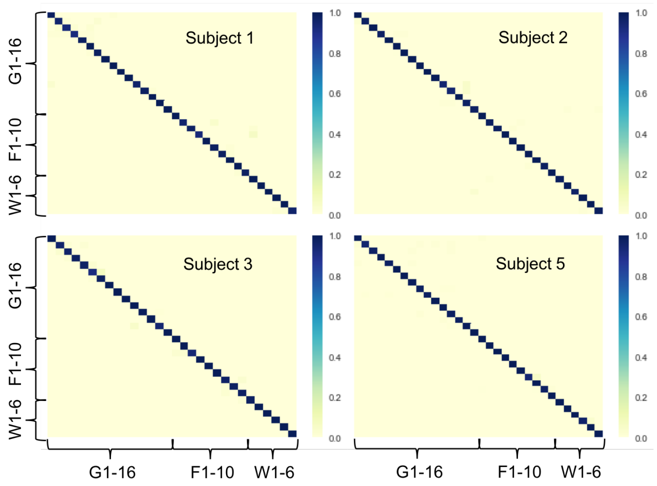


Fig. 7: Prediction accuracy for each subject as a function of algorithm.

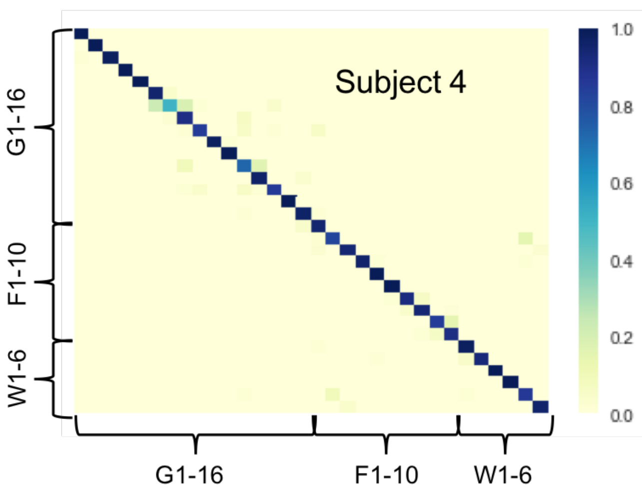
In general, RF was able to generate accurate predictive results for grasps used. However, there are steep hurdles to be faced when developing a model for human subjects. It is very rare for humans to gesture in precisely the same manner repeatedly unless it is a gesture that they have been trained to do. Indeed, even though the on-board 9 DOF IMU was not used in the models, its data indicated that in some grasps, the angle at which objects were grabbed varied significantly between recorded instances, which was reflected by differences observed in the capacitive readings. It is possible that an additional 9 DOF IMU mounted on the hand could be used to examine differences in hand position as related to forearm and correct for or provide more accurate measurement of grasp and position.

Aside from variability of grasps within a test, some subjects had specific patterns of misclassification which could be related to their individual attributes. For subject 2, there was slight difficulty in interpreting grasps G13, G14, and G15 (fingertip on puck, palm on puck, and palm on sphere respectively). It is possible that the subject's hand size in relation to that of the puck and sphere was such that the grasps used were very similar. For subject 3, it was noted that some confusion existed between F7 and F8. The subject indicated that they had difficulty independently hyperextending their middle finger without moving index finger. In future tests, finger hyperextension are done from a closed fist may prove easier for subjects and present a more accurate signal.

The one subject for which significant confusion was seen was Subject 4. Of the subjects tested, they had the smallest circumference at all points along the arm, and in order to obtain a snug fit, many of the electrode straps had to be pulled tight enough to overlap themselves. This may have led to interference in obtaining a clean signal. It is possible that future work with this individual using shorter straps could yield a more accurate result. They also had the shortest forearm, which could indicate that strap placement may need



(a)



(b)

Fig. 8: (a) Confusion matrices for subjects 1-3 and 5. These subjects all had very high prediction accuracies. (b) Close-up of confusion matrix for subject 4. This subject had poorer accuracy as seen in grasps, finger motions, and wrist motions.

to be based on percentage of overall arm length rather than the fixed spacing used in this study.

C. Intra-subject accuracy

Universal modelling between subjects proved to be very inaccurate with SVM generating the highest accuracy at 12%. It was noted however that grasps from the Cutkosky Grasp Taxonomy had a higher accuracy than total set of data. This is not entirely a surprise as other technologies such as IMU [22] and EMG [23] have also had difficulty in identifying grasps and gestures between individuals. This other work has focused on motion primitives as a possible way to overcome the limitations of subject-specific grasp models. To evaluate why difficulty occurred in finding a global model, the importance assigned to individual sensor straps in each subject by the RF algorithm was investigated. The importance assigned to each strap is shown in Table I.

TABLE I: Sensor strap feature importance in model by subject

Subject	Straps listed in order of importance						
	1	2	3	4	5	6	7
1	5	7	4	6	3	2	1
2	1	6	2	3	7	5	4
3	4	2	7	3	1	6	5
4	2	3	1	5	6	7	4
5	1	2	6	7	3	5	4

There does not seem to be any specific pattern regarding which sensor straps are most important in predicting grasps. Two possible explanations for this include: a) the different subjects used their muscles in very different manners making it difficult to translate models between subjects, and b) the sensor straps were tightened to a point which was deemed qualitatively comfortable by individual subjects resulting in variability between individual straps on subjects. One possible way to verify whether the underlying difference was due to strap tightness or muscle utilization would be to do two separate trials per subject on different days and evaluate similarity of models.

V. Conclusions

A proof of concept for a novel method of performing gesture recognition using CT has been created and demonstrated to have high ($95.6 \pm 0.06\%$) accuracy for individual subjects within a range of 16 grasps and 16 individual joint motions. The armband is simple, low cost, easy to use, and robust. This initial study demonstrates accuracy comparable with recent studies using conventional technologies such as FMG ($94.2 \pm 3.0\%$) and EMG ($84.1 \pm 8.6\%$ accuracy) [6].

While the device has performed well in categorizing end points of gestures, it remains to be seen whether real time analysis is within its capabilities. The protocol in this experiment involved manually labelling data recorded while holding a static gesture, and is unlikely to answer this question. Future studies using the IMU to determine relative hand and arm positions and buttons to automatically record finger contact would allow a more robust investigation of gesture recognition in a a continuous data set, and could allow for joint angles to be calculated using linear regression methods. Other things of interest in the near future include determining whether results of trials on an individual subject remain consistent between trials, and whether models constructed from one arm of a healthy individual can accurately predict gesture on the other arm. If this is the case, then it may be possible to use the healthy arm as a trainer for a therapeutic robotics and assistive devices as it would indicate specific differences between motion in healthy and impaired limbs. Testing on a variety of different sized subjects could shed light as to whether fixed spacing is viable, or whether sensor spacing needs to be a function of subjects arm size.

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