Virtual Numpad Design for On-the-Go Calculator using EMG Signals

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***Abstract*—Virtualization and augmented reality is becoming a way of life. This project proposes to design a virtual number pad using EMG signals. The movement of muscles result in electrical pulses that are detected to identify gestures and predict the number that was desired by the user. The project aims to accurately distinguish between very close and fine movement of fingers by the user while typing on a flat, empty surface. The current implementations for similar applications have been done using camera sensors, and shadow detection, the aim therefore, is to use no such hardware and based purely on biological signals with the aid of machine learning algorithms.**

***Keywords*—** EMG signals, finger movements, SVM, decision tree algorithms

I. INTRODUCTION

Virtual keyboards have been an alternate interfacing to computers for quite a while now. It offers advantages to users with disabilities who cannot use a conventional keyboard, or for bi- or multi-lingual users who switch frequently between different character sets or alphabets, which may be confusing over time. The need for a dedicated hardware is eliminated and makes room for improved, and personalized interfacing systems.

The current implementation of a virtual keyboard can be broadly classified into the following types. Most commonly found is the keyboard with a touchscreen layout or areas that sense a key press. Optical projections that project a keyboard layout and contain a sensing mechanism is another solution. Detecting human finger and its motion based on optical, shadow detection is a fairly recent development. Keyboards available online that can be operated through a mouse press, and are independent of the OS they run on is mostly used for quick fixes. Use of other hardware interfaces such as augmented reality, mobile phones, etc, although well explored and have products in the market, use extra hardware that is complex and cost ineffective.

In this project, we propose to accomplish this task using biological signals and cost effective sensors for data collection. The MYO armband is a suitable sensor that can be placed on the forearm of the user. The data of finger movements are captured through the muscle movements at the forearm. This data is filtered, processed and fed to a learning algorithm that learns all its features as shown in fig. 1. Once the learning is complete, the model can be used to predict the incoming data from the user. We also propose a GUI to interact with the user to display the predicted key press. This will also cross validate the intended key press and necessary actions to be taken in case the prediction is false will also be detailed in the sections below.

II. RELEVANT WORK

The solutions explored and visible in today's market are largely based on visual data processing and finger movement detection. A few projects explore the use of EOG signals and EEG signals combined.

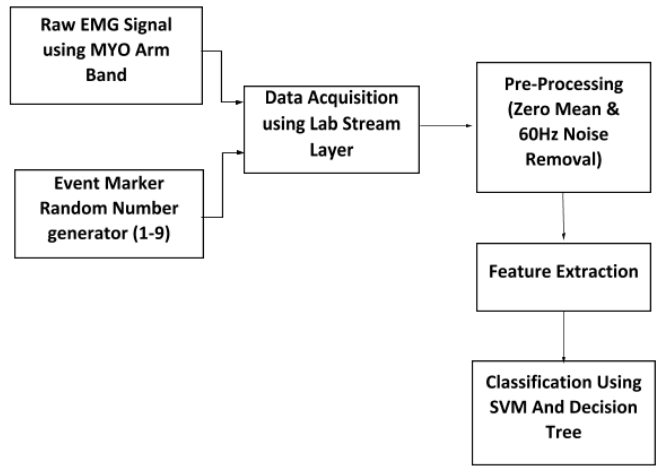

Fig. 1. Data flow block diagram

A. Current Solutions

As mentioned in the previous section, several solutions proposed are optical sensor based. The paper [1] mimics a QWERTY key pad using a 3D optical projector to predict finger movements. The projections from the optical sensor show the user a key board layout. Computer vision algorithms are used to remove background noise and also detect the finger movements of 2 users. Another similar paper [2] proposed a system that is designed for gesture based control of a smartphone without any physical contact, direct line of sight or physical movement. The automated gesture detection is synced to the smart phone thus creating a virtual smartphone that eliminates the need of hardware setup of the mobile device.

Using EOG and EMG biological signals, a virtual keypad [3] is designed with the use of the eye and eyebrow muscle activity. EOG signals are used for navigating between the letters, ie., Eye Gaze controlled Navigation where the direction of the eye movement determines the route for traversal between the letters, and EMG signals are used for clicking the desired letter.

A wearable human machine interface to control the home assistance robot is proposed in this paper [4] The data collected by performing different hand movements is sent as input through WiFi to the motor unit of the assisting robot and the robot moves accordingly. This paper [6] presents an EMG based Computer Interface for the physically disabled people to access the computer without any computer interfaces such as mouse or keyboard. The person can move the cursor or click the desired button on the computer with the help of the muscle movements in the lower arm.

Several such implementations that have been done for various applications have been explored. It is interesting to note that a virtual key board using only EMG signals is yet to be implemented. The project poses a few challenges that will need to be overcome, such as, the finger movements for multiple keys are similar and have very subtle difference between them. The need for more and better feature extraction techniques, reduced noise and removal of artifacts could be critical in determining the success rate of predictions.

B. Feature Extraction for EMG Signals

The importance and scope of feature extraction for a biological signal system is large. A wide set of features are available through the study of similar application ideas. Selecting the right features and processing them is a crucial step to our proposal.

With recent advancements in wireless communication and embedded technologies, wearable electromyographic (EMG) armbands are now commercially available for the general public. The authors of [14] present a variety of features intended for such wearable sensors. The paper also states the importance of sampling rates for data collection of bio signals. Features for EMG signals can also be extracted in time domain as shown in [15], where three features were considered based on statistical features. The features were then evaluated by getting the percentage error of each feature. The paper [16] proposes acquisition and analysis of EMG signals for multiple active hand movements based on wrist-hand mobility for control of prosthesis robotic hand. The features are extracted using statistical analysis to choose the best ones suits for the application.

The paper [5] lists about 14 time domain features that were extracted, out of which 3 were found to be very effective namely Zero Crossing (ZC) frequency, Slope Sign Change (SSC) and the Maximum Fractal Length (MFL). Another paper [7] that suggests time series feature extraction of features such as, Mean Absolute Value (MAV) and Waveform Length (WL). These demonstrate the advantages of using time domain features for an EMG signal. In critical applications such as to identify the neuro-muscular diseases, four new features were extracted in [8]. They are maximum amplitude, phase duration at the maximum amplitude, maximum amplitude times phase duration and number of peaks. The root mean square feature extraction produced better classification accuracy compared to other features such as centroid of frequency and standard deviation in this paper [9].

C. Learning Algorithms: SVM and Decision Tree

Support Vector Machine is one of most widely used supervised learning algorithms for both classification as well as regression problems. SVM is a form of a discriminant function that separates the classes with the optimal decision boundary (line in 2 dimension and hyper-plane in multi dimension) that has the maximum distance between the two classes. If the classes are non linear, they are projected to a higher dimension to make them linear so that the hyper-plane can split them. There are different types of SVM based on distribution of data points.

The deciding factors that contribute to the type of SVM that is used are cost or penalty parameter and gamma parameter. The cost parameter is responsible for the soft or a hard margin hyper-plane. Smaller the value of C, greater is the chance of under fitting /over generalization as the decision boundary does not map some of the data points to its proper class resulting in occurrences of outliers. Higher the value of C, the probability of over fitting increases as it takes into account all the data points to classify correctly. Thus there is always a trade off between choosing the decision boundary wisely and taking care of the outliers. The gamma value specifies the extent to which a single training example creates an impact on the decision boundary. High value of gamma results in the data points closer to the decision boundary to have more weights than the data points farther to it leading to a wiggly decision boundary, whereas if the gamma value is less, the weights are equally divided to all the data points irrespective of their position thus resulting in a more linear decision boundary. Thus on the whole SVM algorithmic approach seems to be one of the most suitable options to classify the EMG signals.

In this paper[10] the EMG signals of six hand movements were analyzed using the wavelet packet transform. The relevant features were extracted using Singular Value Decomposition and the features classified using Multi class SVM with Gaussian Kernel function. The advantage of using the Gaussian kernel was that the number of the support vectors(number of basis function),the centres and the weights are obtained automatically. Testing set showed an accuracy of 96%.

In the paper[11] the lower limb movements were classified based on the EMG signals obtained from each phase of level walking by Multiple Kernel learning methodology which is a combination of SVM and Binary Decision trees. A binary class SVM can be expanded to a multi class SVM by two possible methods such as solving a single optimization problem or combining multiple binary SVMs. The second method was adopted as the decision tree decomposition methodology was a part of the procedure and it reduced the computational complexity as well as increased the accuracy. This paper states that the multi kernel SVM approach showed improvement in accuracy compared to single kernel SVM but it increases the computational load when the number of kernels increased.

An interesting technique for feature extraction by using Convolution Neural Network was proposed in this paper [12]. The first four layers contained convolution layers composed of 64 filters with a stride and a padding of 1. This was in turn followed by 6 fully connected layers in order to maintain the equilibrium between the network and feature extraction. The softmax function as well as a 5 way output layer was used in the end of the network. The last output layer was replaced by SVM classifier. The features obtained by CNN was compared with 3 time domain features and the former had better accuracy than the latter. A research proposed by this paper [13] shows that when SVM-KNN approach is used, even with reduced number of feature extraction, gives an accuracy of 95%.

Decision tree algorithms is another learning and classification tool being used in this project. In decision tree, divide and conquer technique is used as basic learning strategy, with a structure that includes a root node, branches, and leaf nodes. Each internal node denotes a test on an attribute, each branch denotes the outcome of a test, and each leaf node holds a class label. The paper [19] focuses on the various algorithms of Decision tree (ID3, C4.5, CART), their characteristics, challenges, advantage and disadvantages.

The paper [20] uses decision tree algorithm to create a model that successfully classifies students into one of two categories, depending on their success at the end of their first academic year, and finding meaningful variables affecting their success. Several classification algorithms for constructing decision trees have been compared and the statistical significance (t-test) of the results was analyzed. Finally, the algorithm that produced the highest accuracy was chosen as the most successful algorithm for modeling the academic success of students. The highest classification rate of 79% was produced using the REPTree decision tree algorithm.

III. EXPERIMENTAL SETUP

The sections below detail the experimental setup used for data collection, the pre-processing techniques used and the types of classification requirements in order to predict successfully.

A. Data collection

The collection of EMG signals for the proposed idea is done using MYO arm band [17]. The arm band is placed on the forearm, and consists of sensors that send data over 8 channels. Figure 2 shows the raw data over one channel. The sampling frequency of MYO band is 200 Hz. The data is collected using Lab Stream Layer (LSL), which time stamps every data point. A random number from one to nine is generated and printed on the GUI. The user views the number and tries to mimic the typing of that number. LSL also provides option to record event marking over the incoming bio signal. The random

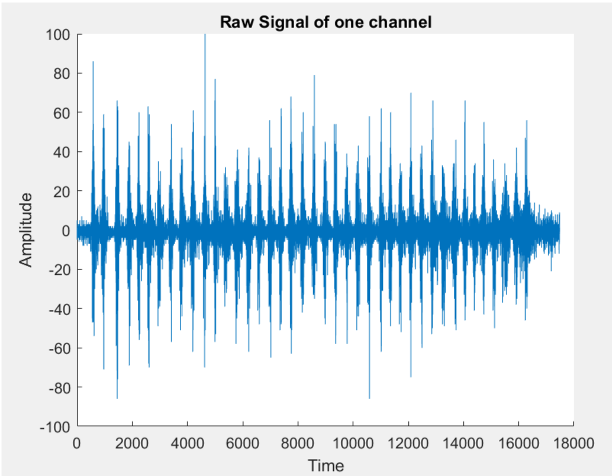

Fig. 2. The raw signal obtained using MYO arm band

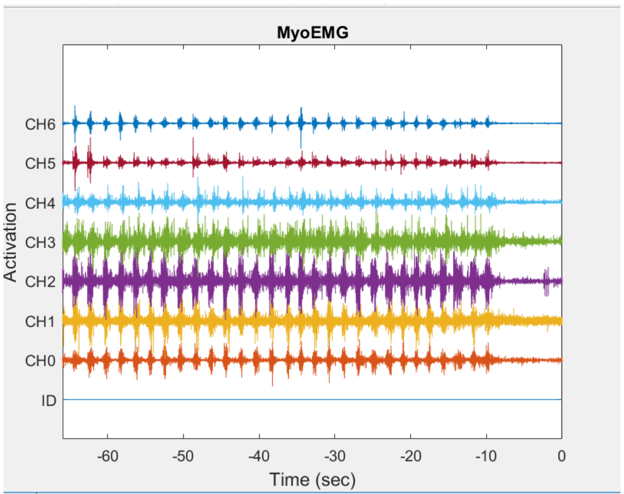

Fig. 3. Real time visualization of raw EMG data over 8 channels

number generated is sent to LSL while simultaneously printing it for the user.

LSL therefore has two incoming signals, the bio signal from MYO arm band and the random number from the GUI. Both the data signals are stored continuously with time stamps. The time stamp of the incoming random number is matched with that of the raw EMG signals, and subsequent 600 samples are taken for pre-processing. This is because we consider the user to spend 3 seconds performing the gesture, and based on the sampling rate of 200 Hz, we select 600 samples to contain relevant information for each gesture. The GUI then will wait for a period of 5 seconds, display and send the next random number.

Furthermore, for ease of data collection, viz_stream, as seen in figure 3, is used in MATLAB that helps stream the data in real time. This can ensure that we record the right data by visualizing the data while it is being recorded.

B. Pre-processing

The data once sampled into the required sets is pre-processed before extracting features from them. This is due to the presence of noise in the bio signals. Noise can be induced into the signal from multiple sources that can be external, such as the AC/DC power input, the frequency components due to lights, etc. These sources can also be internal such as the thermal noise of the device, etc. The noise removal is a critical part of using bio signals for building applications. This is because the classification learners will end up learning the noise as well, and can lead to false prediction.

The first part of noise removal is zero-meaning, where the noise at 0 Hz is removed. The next part of noise removal is the noise at 60 Hz. We are using a butter-worth filter to remove noise from 59.5 Hz to 60.5 Hz. The filter parameters are, sampling frequency $fs = 200Hz$, cut-off frequency $fc = 60Hz$.

C. Feature Extraction

Several papers have been studied as mentioned above, and the features to be extracted for our data have been narrowed to the following:

- Root Mean Square (RMS) is the deviation of the signal from its mean given by the formula,

  $$\sqrt{1/N-1(\sum_{n=1}^{N-1}[X_i-X]^2}$$

  where X_i is the current data point and X is the mean value, and N is the total number of samples
- Variance is the average of the squares of the mean values given by,

  $$1/N-1(\sum_{n=1}^{N}[X_i]^2$$

- Difference Absolute Standard Deviation Value that represents the standard deviation value of the wavelength,

  $$\sqrt{1/N-1(\sum_{n=1}^{N-1}[X_{i+1}-X_i]^2}$$

- Maximum Fractal Length for measuring low level muscle activity.

  $$log(\sqrt{\sum_{n=1}^{N-1}[X_{i+1}-X_i]^2})$$

- Average Amplitude Change contains information about the frequency, amplitude and duration of the signal

  $$1/N(\sum_{n=1}^{N-1}[X_{i+1}-X_i]$$

Figure 4 shows the plot of an extracted feature for the processed EMG data.

IV. EXPECTED RESULTS

Although there has been extensive work done in this field, there has not been any design of a virtual key board using EMG signals alone. Due to this, it is important for us to consider the right features, and the classification algorithms for predicting the actions successfully. One way to achieve this is to test the chosen classification algorithms of a pre-obtained data set from an open source repository.

A. Testing Using Standard Data Set

The data set by the paper [18] was used, and the results obtained were compared with the results claimed in the paper, to test the performance of the chosen algorithms. This data consists of 6 gestures that were recorded over a sample of 3000 data points per each gesture. The data was loaded into MATLAB, and the above mentioned features were extracted.

Figure. 5 shows the scatter plot of two features for the 6 gestures. Once the features have been extracted, the data is fed to the classification learner. Principal component analysis will be used to reduce the number of features at a later stage. The trained data produced an accuracy of about 96% for SVM and about 91% for simple tree. When PCA was enabled, the accuracy for SVM and decision tree was about 94% and 88% respectively.

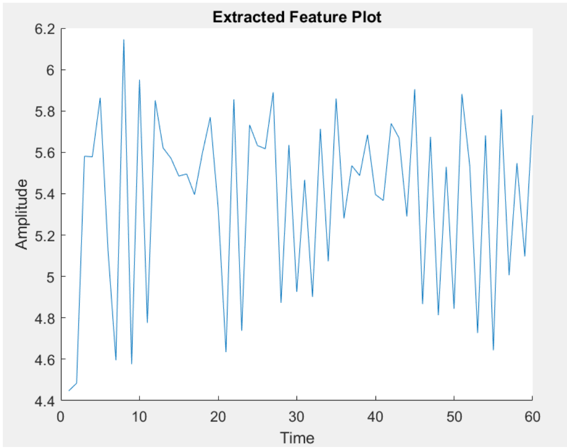

Fig. 4. Plot of extracted feature for pre-processed EMG data

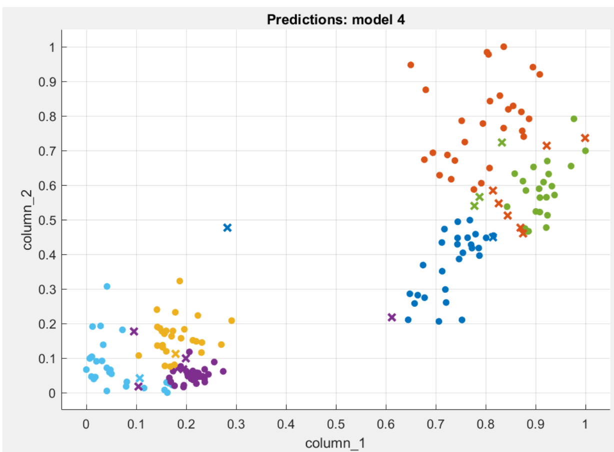

Fig. 5. Scatter plot of two feature for the 6 gestures

The remaining portion of the data was tested and a confusion matrix based on the trained set was produced as shown in figure. 6.

Based on these feature extractions and the chosen classification algorithms, the data is expected to predict the key press intended by the user in real time. The event markers will aid in selecting the continuous raw signal, and the processing that follows will derive the required features. Also, the training set will consist of random number gestures so that the learning is not biased towards any one gesture.

V. CURRENT IMPLEMENTATION

Our proposed method includes the design of a GUI that displays the predicted class as the gesture is being performed by the user. The MYO armband has been the choice of hardware to collect EMG signals. It has 8 channels from which we can obtain the signal information. The data acquisition of EMG signals as well as event markers is done using the Lab Stream layer. The event marker is used to pin point the exact time where the EMG signal has gesture data. This is used to get accurate data sets for training the model. A random number generator has been used that sends out numbers from 0-9, which also acts as our class labels during training. Both the signals along with their time stamps are recorded through LSL. We then compare the time stamps of the EMG signals and the time stamp

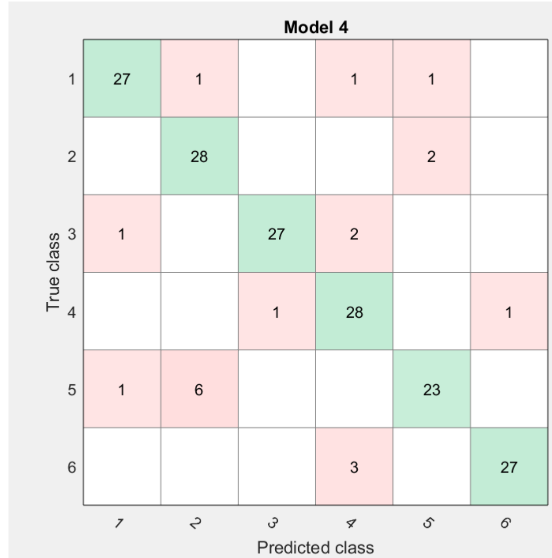

Fig. 6. Confusion matrix for the trained data set

of the event marker in order to sync the data. Once the time stamps are synced, 600 samples from that point are stored into the buffer. One data chunk contains 600 data points from the 8 channels. This is because the MYO armband has a sampling frequency of 200 Hz and the used us given a buffer of 3 seconds to perform the gesture.

The signal is then pre-processed to remove noise at zero Hz and 60 hz. This is followed by feature extraction where only relevant features are taken into consideration which play a crucial role in distinguishing the finger movements relative to each number. We have used 5 features as described in the above sections. The mean of the EMG signal is considered close to zero. Difference Absolute Standard Deviation value describes about the standard deviation of the wavelength. We have used Maximum Fractal length which calculates the lower level muscle activity. Average Amplitude Change determines the amplitude, frequency and time duration of the EMG signal. The extracted signal is then fed to the classification learner tool box to classify based on Support Vector Machine and Decision tree algorithms.

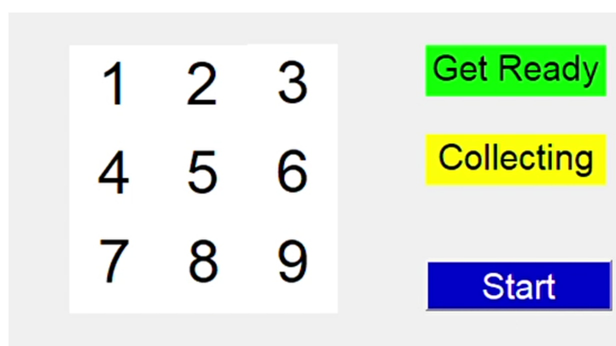

Fig. 7. Real time implementation GUI

The real time implementation follows a similar procedure as the offline data collection. However, the data is divided into chunks based on a windowing process. The User performs a gesture upon seeing the visual indication from the GUI as shown in fig.7. The data is pulled sample by sample for a duration of 3 seconds. 600 samples are buffered and sent to the pre-processor. After this, features

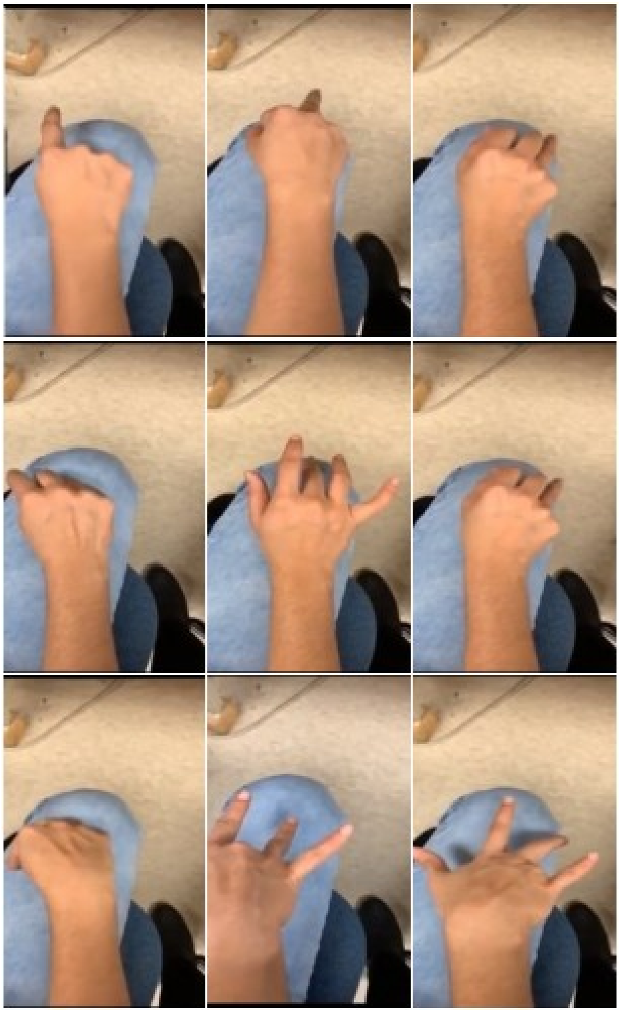

Fig. 8. Gestures performed for each numbers

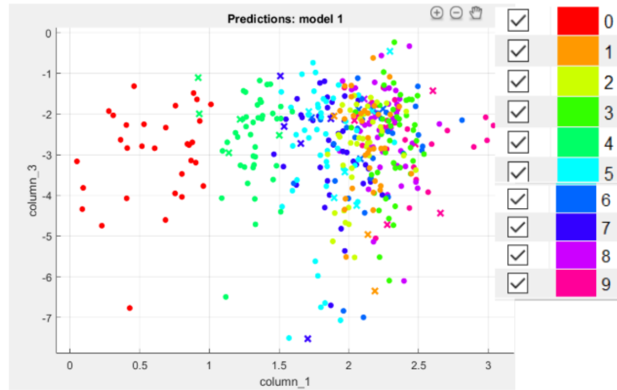

Fig. 9. Scatter Plot of two features for 10 gestures

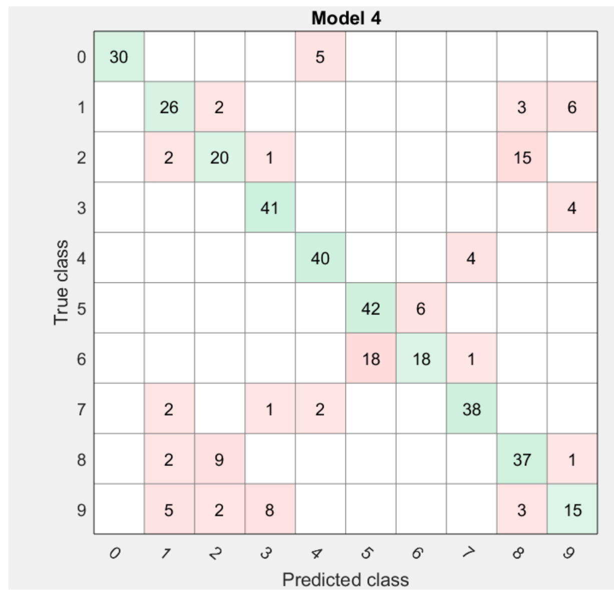

Fig. 10. Confusion matrix of the current implementation

are extracted and it is sent to the prediction model. The output is displayed on the GUI for the user. Fig 8 shows the various gestured performed for training the model as well as during real time prediction.

VI. RESULTS AND DISCUSSION

The use of EMG signals or any bio signals for that matter induces challenges in generalizing the trained model. We were able to obtain an offline accuracy of 92.7 % for SVM and 85.8 % for Decision Tree algorithms. The accuracy was a reduced in the real time however with a rate of 66 % and this can be analyzed through the scatter plot and confusion matrix shown in figure.5 and figure10 respectively. Initially we faced an issue with the trained model getting biased to a specific number and hence it was predicting the same number most of the time. This issue was solved by collecting the gestures for each numbers in a randomized fashion.

As the EMG signals from the same muscle are subject to change due to various factors such as muscle fatigue which is caused due to the strain imposed in the muscle by repeatedly carrying out the same task we had collected the data in over multiple days thereby avoiding changes in EMG signals due to fatigue.

We performed gestures using fore, middle and ring fingers. Fore-finger was used for classifying numbers 1, 3 and 7, middle finger for 2, 4 and 8 and ring for 3, 6 and 9. Using the same finger for classifying the numbers resulted in sometimes predicting incorrect values as the gestures were somewhat similar except for a slight variation in the y direction resulting in only minute differences in the muscle movements. The figure. 8 shows the gesture performed for different numbers. The scatter plot in figure. 5 depicts the classes that are closely spaced which gives room for mis-classification.The reject class 0 is very distinct compared to the other classes as shown in the scatter plot. The confusion matrix in figure. 10 clearly specifies the number of correct and incorrect classes. The class 6 has most number of incorrectly predicted output, while class 7 is often predicted as 1. The class 6 was often predicted as 5, due to the same muscle extensor digitorum being used to send signal to both the middle and ring finger.

VII. CONCLUSION

Virtual Number pad using EMG signals was proposed and implemented in this paper. The project is very handy, flexible, easily configured and can be customized to meet the needs of the person. Previous implementations were explored and they use camera, light/shadow sensors, software keyboards that need mouse clicks or some sort signal inputs and image processing algorithms. Our implementation proposes the use of MYO armband as the only hardware required. The software consists of the signal processing and trained model for prediction. Our future work aims to increase the accuracy and extend the number pad to a virtual keyboard for users on the go. We also wish the reduce the latency that has been introduced to give the user time to think of a number and perform the gesture. Once the model is made robust, this delay can be reduced to real time typing speed.

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