Effect of Analysis Window and Feature Selection on Classification of Hand Movements Using EMG Signal

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Abstract. Electromyography (EMG) signals have been successfully employed for driving prosthetic limbs of a single or double degree of freedom. This principle works by using the amplitude of the EMG signals to decide between one or two simpler movements. This method underperforms as compare to the contemporary advances done at the mechanical, electronics, and robotics end, and it lacks intuition. Recently, research on myoelectric control based on pattern recognition (PR) shows promising results with the aid of machine learning classifiers. Using the approach termed as, EMG-PR, EMG signals are divided into analysis windows, and features are extracted for each window. These features are then fed to the machine learning classifiers as input. By offering multiple class movements and intuitive control, this method has the potential to power an amputated subject to perform everyday life movements. In this paper, we investigate the effect of the analysis window and feature selection on classification accuracy of different hand and wrist movements using time-domain features. We show that effective data preprocessing and optimum feature selection helps to improve the classification accuracy of hand movements. We use publicly available hand and wrist gesture dataset of 40 intact subjects for experimentation. Results computed using different classification algorithms show that the proposed preprocessing and features selection outperforms the baseline and achieve up to 98% classification accuracy.

Keywords: EMG, Prosthetic Limbs, EMG-PR, Classification, Features
1 Introduction

Biosignals are the electrical activity generated by an organ that represents a physical activity. These biosignals aided by the contemporary advancement in the fields of microelectronics and engineering is being used for various biomedical applications. More computationally efficient machines have seen an increasing trend in the interfaces based on these signals in brain-computer interaction (BCI) as part of the human-computer interface (HCI) [10]. The most commonly used biosignals are Electroencephalography (EEG) and Electromyography (EMG). These Biosignals, in general and EMG signals in particular are used for the control of assistive devices for physically impaired people. EMG are signals which are generated by the muscle contraction representing a neuromuscular activity [12][11]. These signals can be acquired either invasively or non-invasively. In the case of non-invasive EMG, the signal is also called surface EMG (sEMG). These signals are acquired by placing the electrodes on the skin of the subject (human). In invasive EMG, signals are acquired intravenously using needle electrodes. Although invasive EMG is attenuated to certain problems associated with sEMG, such as muscle cross-talk, it has its own shortcomings. These deficiencies include minor tissue damage and the reluctancy of people to the use of needles. The problem of muscle cross-talk can be accounted for by using better quality electrodes.

Method to operate myoelectric control has been around for more than five decades, such as Proportionally control strategy. However, these devices offer single or a two degree of freedom (DOF) and offer restricted intuitive control [9]. More recently, Pattern recognition (PR) based EMG addresses the shortcomings of the proportional controlled, such as the dexterity involved with the conventional method [15].

EMG-PR based control strategy works on the principle that the EMG signals are distinct for a muscular activity mainly involving the upper limb. These signals are classified using machine learning techniques to decode the amputee’s intended motion. The overall method is shown in Figure 1. Despite the recent advances in signal classification for the activation of the prosthetic limb, this method is still not clinically viable. This is mainly due to the lack of optimal signal processing strategies, appropriate feature selection, and signal classification. The intricacies involved with the control system of EMG-PR often leads the patient to opt for the conventional prosthesis. About one-third of the amputees reject the self-powered prostheses [2].

The obstacle that is obfuscating the final goal of powering a prosthetic limb using sEMG signals is to find the optimum pre-processing and features selection that needs to be done to the signal to extract the features which can be feed to the classifier for accurate classification. Accurate prediction of hand movements involves fine data pre-processing, using appropriate analysis window length from which optimal features are extracted, and lastly the choice of the classifier. Several works have explored different analysis window length and different kinds of pre-processing techniques along with finding the optimal features to increase classification accuracy. Authors in [20] used principal component analysis for
In this paper, we investigated the effect of pre-processing of the raw data (signal) and variate the analysis window length to compute the accuracy of the hand movements. We also investigate the impact of feature selection on efficiency. We compare our proposed technique with several baselines \cite{3,14} and show that our proposed method outperforms them in terms of classification accuracy. For the baseline methods, we use the analysis window length and pre-processing techniques as mentioned in the original studies. We apply four different classification algorithms to compute accuracies. Our main contribution are as following:

– We show that effective preprocessing helps to improve the classification accuracy of the underlying signal.
– We show that optimum size of analysis window is important to increase the overall performance of the approach.
– We show that selecting optimum combination of features further helps to improve the performance.

The rest of the paper is organized as follows. In Section 2 we discuss the related work related to the EMG. Our proposed solution is mentioned in Section 3. Experimental settings, dataset description along with its preprocessing, and different configurations of feature is given in Section 4. Results of our proposed method are given in Section 5. We conclude the paper in Section 6.
2 Related Work

Previously, a dataset called Ninapro has been introduced by [4], which was made public in the year 2014. At the start, it had three databases, namely database 1 (DB1), database 2 (DB2), and database 3 (DB3). To date, it contains 8 databases. This dataset is used in various works for the classification of hand movements. Authors in [14] used the database (DB2) for the first 11 subjects to classify 17 different hand and rest movements. They used a window size of 256ms with an increment of 10ms. They have used different configurations of seventeen time-domain features, with different classifiers (K Nearest neighbor, Random forest, and SVM). They reported that the Random forest achieves the highest accuracy, with an average classification accuracy of 90%. They used a moving average for windows analysis in which the moving average of consecutive five windows. However, taking the average of multiple windows affected their classification accuracy because it averages out the important signal information in the time domain. Also, as they only used data of 11 subjects, which is much smaller. In a more recent work [5], data of 40 subjects of DB2 of Ninapro dataset was used. Four different time-domain features, with a window size of 200ms along with an increment of 10ms was used. The classifier “Extreme leaning machine” was used for classification. Their average classification accuracy was 79%. This work, although is comparatively better as the number of subjects used, however, their selection of window size is not optimum. In a similar work [21], authors used DB2 of the Ninapro dataset for all 40 intact subjects and 50 exercise, with a window size of 256ms. They used a convolution neural network for classification. Their average classification accuracy was 78%. However, the runtime of the convolution neural network was the main problem with their approach.

In [13], the authors used 11 intact subjects of DB2 along with 9 amputated subjects of the Ninapro dataset. They used the same analysis window configuration as that of the [14] and used time-frequency domain features by using the discrete wavelet transform of the data. They used the random forest algorithm to compute classification accuracy. They achieved 90% accuracy for intact subjects and 75% for amputated subjects. Since discrete wavelet features require the transformation of the signal, the approach proposed is computationally expensive. This is because the micro-controller embedded in the prosthetic limb has limited computational power, which makes this method obsolete in real-life usage. Authors in [20] used DB2 of Ninapro data set. They used data of 40 subjects for classification of sEMG signals using spectrogram with an analysis window length of 200ms and an increment of 100ms. The spectrogram was computed using 256 points Fast Fourier transform using a hamming window of 256 points with an increment of 184 points. To reduce the dimensions of the spectrogram, they used principal component analysis. They achieved 75.74% average classification accuracy. In [3], data of all 40 subject is used of DB2 for 50 movements using the parameters used in [7,6]. Their average classification accuracy is 75.27%.

Authors in [1] used two channels to classify combined finger movements, using the “Extreme learning machine” for classification, with accuracy up to 98%. However, they have used only two surface electrodes, which make it less viable for
clinical usage because two electrodes are not enough to record the motor activity. Authors in [19] managed to achieve an accuracy of more than 90% by using 32 channels sEMG for classification of 10 finger movements. In [22], the effect of various machine learning classifiers on the accuracy is analyzed. More recently, authors in [8] used sEMG data of 48 subjects for classification of movements. However, only four hand movements were considered in their experiments.

3 Proposed Solution

The sEMG signals are dynamic in nature (it vary quite fastly). Therefore, to encapture and analyze these signals, overlapped window is used, which slides over the data with a predefined size and a predefined increment $w$ (see Figure 2). Characteristics of the window play an important role in feature extraction, which in turn affects the classification accuracy.

In our proposed approach, we used a window size of 256ms and with an increment of 10ms, which ensures that the threshold of 300ms is not crossed, a size of the window that will induce a delay that a user might detect [6]. The window size of 256 ensures that a dense array of raw data is captured. Data samples corresponding to the size of 256ms window length are stacked in a row vector for each sensor, thus producing a segment of sEMG data. A total of 12 sensors are used to record sEMG data. This resulted in a matrix of dimension $N \times (M \times 12)$, where $N$ is the total number of windows, and $M$ is the number of sEMG voltage data samples that are in one window. Features were extracted from each window resulting in a feature matrix $F$ of dimensions $N \times P$, where $P$ is the number of features. This feature matrix is then given as input to the classification algorithms.

**Analysis Window:** Due to the random nature of the sEMG signal, it’s instantaneous value has almost no content to offer. For real time analysis of the sEMG signal, analysis window is used as used previously by [18]. There are two kind of analysis window, which are mostly used in pattern recognition based systems, (i) adjacent window, and (ii) overlapping window. In (i), a predefined length of windows is taken, and next window starts at the end of preceding window, from these window signal features are extracted. However, it does not generate a dense array of signal, as in case of adjacent window, the processing resources are underutilized. In Overlapping window analysis, a pre-defined window length is taken, which slides over the signal with an increment size that is less than the original window size. This generate a dense array and make full use of the available processing power [16]. Figure 2 shows the overlapped window technique for a given EMG signal.

The size of window has a direct relationship with the accuracy. The greater window size is better to achieve higher classification accuracy. However, greater window size is more expensive in terms of computational overhead. The effect of window size is studied in [17]. Authors in [17] discover that the upper limit for the window size must be $300\text{ms}$ . The optimal window size for overlapped
window technique has been investigated by various researchers and found to be in the be greater than 200ms [18]. In this paper, we used a window size of 256ms with an increment of 10ms. This ensures that we have a dense array of windows from which we can extract features.

**Feature Selection** The problem in successfully implementing a myoelectric control prosthesis is that sEMG signals contain high dimensional data. To reduce the dimensions of data, features are extracted from the data, which can preserve the information of the signals. In literature, Various time domain features have been explored, which provides good classification accuracy. For instance, integrated EMG. Mean absolute value, Simple Square Integral, Variance of EMG, Root mean square, Zero Crossing, Average Amplitude Change, and Willison Amplitude. For our experiments, we extracted Zero Crossing, Mean absolute value, Slope Sign changes, Mean absolute value Slope, Waveform Length, Root Mean square, and 20 frequency bins of histogram. A feature matrix from the window of these 26 features were made for each sensor thus a total 312 features were made for each subject.

We used different configurations (combinations of features) to compute the accuracies. Our goal is to find the best configuration so that dimensions of data can be decreased while increasing the classification accuracy. The configurations of features are given in Table 1. In configuration C1, we used all 26 features, while different combinations of features are used other configurations (from C2 to C7). In order to make for fair comparison with the baselines, we selected same features for the baselines as well.
Table 1: List of features and the different configurations “C1 to C7” (combinations of features) used in our experiments

| Features              | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|-----------------------|----|----|----|----|----|----|----|
| Mean Abs Value        | ✓  |    |    |    |    |    |    |
| Mean Abs Value Slope  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  |
| Waveform Length       | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  |
| Slope Sign Changes    | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  |
| Zero Crossing         | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  |
| Histogram             | ✓  |    |    |    |    |    |    |
| RMS                   | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  |

3.1 Choice of Classifier

In this paper, we use multiple classifiers and overall achieve greater accuracy without aggregating the window (moving average) (aggregation is done in [14]). We used four classifiers, namely k Nearest Neighbors (kNN), Random Forest (RF), Support Vector Machine (SVM), and Naive Bayes (NB).

4 Experimental Evaluation

In this section, we describe the dataset and baseline methods. The classification of hand movements is performed using R studio. All experiments are performed on the core i5 system with 4GB memory.

4.1 Dataset Description and Performance Measure

The data used in this paper is called Non-Invasive Adaptive Hand Prosthetics (Ninpro Project[^4]) for sEMG signals for both intact and amputee subjects [14]. Currently, it contains 8 database having data of 130 subjects (117 intact subjects and 13 trans-radial amputated subjects). Subjects perform series of wrist, hand, and finger movements (see Figure 3). The data is generated in a controlled environment to avoid any noise. For experiments, we used DB2 of Ninapro, which contains a total of 40 intact subjects data. A total of 50 movements were performed by intact subjects in DB2. These movements are further sub-categorized into E1, E2, and E3, each corresponding to different movement table. In this paper, we are using E1, which contains data of 17 movements, which are given in Figure 3.

The acquisition setup for DB2 includes electrodes to record muscular activity. In the dataset, 12 delsys double-differential sEng electrodes with a base station were used to record sEMG signals. Out of the 12 electrodes, eight were placed at a fixed radius around the forearm at the elevation of the radio-humeral joint. Furthermore, 2 electrodes were placed on the biceps brachii and triceps brachii.

[^4]: http://ninaweb.hevs.ch/
Lastly, palpation was used to place the remaining two electrodes on the main activity spots to find the anterior and posterior of the forearm. After giving consent and physiological information such as age, height, and gender, each subject was asked to mimic a series of movements shown to them on a screen, which they performed 6 times. The interval of each movement’s repetition was 5 seconds, followed by a reset period of 3 seconds in which the subject was at rest state.

The data was sampled at a rate of $2kHz$. The raw sEMG signals are prone to noise (i.e. Power-Line noise), and therefore they were cleaned from $50Hz$. The data was relabeled to rectify the mismatching in the movement competition time. Dataset statistics are given in Table 2.

| Statistics                                      | Database 2 |
|-------------------------------------------------|------------|
| Intact Subjects                                 | 40         |
| sEMG Electrodes                                 | 12 Delsys  |
| Total Number of Movements (rest included)       | 50         |
| Number of Movement Repetitions                  | 6          |
| E1 (Exercise B) “Number of Movements”           | 17         |

Table 2: Ninapro Dataset Statistics

4.2 Baseline Methods

For the first baseline method, we implemented the work of [14] with an overlapped window of size 256ms and an increment of 10 ms. Then average of 5 consecutive windows are taken (see Equation (1)). The disadvantage of taking the average of multiple windows is that it averaged out (distorted) the useful information in the signal, which in turn can affect the classification accuracy. We call this technique as “Aggregation Window” (AG) technique.

$$WG_t = \frac{1}{n} \sum_{k=1}^{n} S_{nt-k} \quad (1)$$
Where \( n \) is the average of five windows, and \( S_{nt-k} \) is one window segment.

The second approach, which we are using as a baseline, is proposed in [3]. To implement the work of [3], data of 40 subjects of DB2 was used. This data is segmented into the overlapped window of size 200ms. This approach does not aggregate the analysis window. Therefore, we call this technique as “Without Aggregation” (WA) technique.

4.3 Performance Measure

To evaluate our proposed method, we compute accuracy for each subject (and each configuration) separately and compare them with the accuracies of the baseline methods. We also report average classification accuracy (average of every 10 subjects) of our method and compare them with the average accuracies of the baselines.

5 Results and Discussion

In this section, we report the results of our proposed approach for different configurations and compare the results with those computed for the baselines.

Results for subjects 1 to 10, 11 to 20, 21 to 30, and 31 to 40 are shown in Table 3, 4, 5, and 6 respectively. The bold values show the maximum accuracy. We can see that our proposed approach (C1) outperforms the baselines and other configuration methods for most of the subjects. We found that out of four classifiers used, kNN and SVM performed better compared to the other two classifiers. It is evident from the results that the effect of averaging out 5 windows (as done in AG approach) drop of accuracy when compared with other approaches. We found that the configuration C1 outperforms the baselines and all other configurations.

Figure 4 shows the average classification accuracy of 10 subjects each for our proposed methods and the baseline methods (Figure 4 (a) shows average over first 10 subjects, Figure 4 (b) shows average over subjects 11 to 20 and vice versa).

The choice of classifiers has an important effect on the performance, as evident from the results. The SVM and kNN has an average classification accuracy higher than 85% for all subjects and all approaches. The DT and NB are consistently underperform for all methods and all subjects. Hence, their use in the classification of sEMG signals is obsolete. As described earlier, the use of the combination of features significantly affects the dimension of data and classification accuracy. We can see in Figure 4 that although the configuration C1 outperforms all other configurations, the configuration C5 tend to improve the accuracy (with fewer dimensions than C1) as compared to C2, C3, C4, C6, and C7. Therefore, in a scenario where we can afford to drop the accuracy while increasing the computation speed, configuration C5 can be a good choice to consider. It is worth noting that the processor embedded in the micro controller in the prosthesis has a limited amount of processing power. Therefore, to get a quick and real life like
scenario at the cost of a few percent drop in the classification accuracy seems to be a choice that can be opted.

| Classifier | Subjects | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 |
|------------|----------|----|----|----|----|----|----|----|----|----|----|
| **kNN**    | WA       | 97.65 | 97.6 | 97.24 | 95.2 | 97.76 | 93.13 | 97.07 | 98.53 | 97.2 | 97.33 |
|            | AG       | 90.21 | 87.93 | 89.56 | 85.61 | 89.25 | 88.79 | 87.75 | 91.04 | 92.66 | 90.44 |
|            | C1       | **98.34** | **98.18** | **97.75** | **96.29** | **98.31** | **97.21** | **97.58** | **98.61** | **98.24** | **98.18** |
|            | C2       | 92.74 | 88.93 | 94.05 | 83.77 | 96.31 | 88.99 | 92.07 | 89.59 | 94.64 | 92.31 |
|            | C3       | 92.18 | 89.37 | 94.52 | 83.77 | 96.31 | 88.99 | 92.07 | 89.59 | 94.64 | 92.31 |
|            | C4       | 92.07 | 89.14 | 93.02 | 86.41 | 94.80 | 85.98 | 90.39 | 94.31 | 95.86 | 95.86 |
|            | C5       | 82.15 | 84.27 | 83.57 | 84.41 | 87.14 | 87.53 | 65.75 | 76.12 | 87.57 | 88.82 |
|            | C6       | 81.91 | 85.80 | 85.97 | 85.23 | 87.25 | 87.31 | 64.33 | 70.54 | 85.38 | 86.05 |
|            | C7       | 89.9  | 92.71 | 91.71 | 92.87 | 93.11 | 94.61 | 74.09 | 79.22 | 94.22 | 92.64 |
| **NB**     | WA       | 73.20 | 67.84 | 68.81 | 61.25 | 76.76 | 69.32 | 64.00 | 76.80 | 82.68 | 76.24 |
|            | AG       | 50.72 | 38.22 | 42.16 | 41.62 | 51.67 | 43.50 | 45.41 | 51.65 | 51.16 | 48.84 |
|            | C1       | **74.23** | **69.59** | **70.15** | **63.70** | **77.71** | **72.45** | **66.40** | **79.80** | **84.62** | **77.57** |
|            | C2       | 32.11 | 22.90 | 28.58 | 17.60 | 37.64 | 34.67 | 26.05 | 31.13 | 39.29 | 31.62 |
|            | C3       | 32.88 | 21.43 | 34.81 | 14.44 | 33.72 | 30.42 | 30.33 | 29.45 | 34.38 | 28.44 |
|            | C4       | 37.48 | 25.94 | 40.36 | 21.28 | 36.75 | 32.94 | 35.71 | 43.81 | 34.49 | 34.49 |
|            | C5       | 43.88 | 36.43 | 45.71 | 28.05 | 51.24 | 44.23 | 36.99 | 44.46 | 53.31 | 45.80 |
|            | C6       | 43.28 | 38.04 | 43.72 | 26.49 | 51.21 | 42.83 | 38.01 | 45.73 | 55.82 | 44.66 |
|            | C7       | 43.6  | 36.37 | 45.18 | 29.28 | 51.28 | 41.65 | 38.7 | 47.04 | 54.28 | 45.35 |
| **DT**     | WA       | 57.02 | 44.56 | 51.89 | 44.83 | 47.69 | 46.70 | 42.15 | 57.03 | 51.15 | 43.89 |
|            | AG       | 27.85 | 25.21 | 28.61 | 34.83 | 28.47 | 30.81 | 34.06 | 27.83 | 34.28 | 30.26 |
|            | C1       | 31.25 | 44.32 | 49.57 | 38.66 | 48.84 | 46.83 | 43.04 | 57.99 | 67.19 | 41.42 |
|            | C2       | 28.72 | 24.82 | 39.94 | 23.75 | 39.31 | 38.02 | 29.08 | 34.46 | 42.90 | 32.66 |
|            | C3       | 36.99 | 27.14 | 33.79 | 21.32 | 41.00 | 32.64 | 32.61 | 30.11 | 38.51 | 33.56 |
|            | C4       | 35.42 | 33.30 | 44.56 | 30.67 | 47.85 | 40.09 | 33.53 | 27.28 | 39.55 | 28.23 |
|            | C5       | 40.03 | 36.28 | 44.44 | 25.62 | 42.47 | 40.61 | 32.36 | 45.21 | 48.24 | 39.52 |
|            | C6       | 38.43 | 34.02 | 40.47 | 23.06 | 44.34 | 36.99 | 34.40 | 30.99 | 45.84 | 41.76 |
|            | C7       | 43.2  | 34.14 | 45.84 | 35.17 | 51.46 | 39.41 | 36.11 | 41.43 | 46.06 | 37.94 |
| **SVM**    | WA       | 89.43 | 88.78 | 90.13 | 89.50 | 94.02 | 93.01 | 87.88 | 95.40 | 93.28 | 93.47 |
|            | AG       | **94.77** | **93.87** | **93.64** | **92.93** | **95.56** | **94.60** | **95.49** | **96.04** | **95.98** | **95.09** |
|            | C1       | 93.89 | **94.33** | **94.98** | **93.91** | **96.05** | **95.56** | **93.13** | **97.62** | **96.77** | 96.34 |
|            | C2       | 73.78 | 62.56 | 74.28 | 56.04 | 78.97 | 63.64 | 48.17 | 64.51 | 77.63 | 72.74 |
|            | C3       | 80.49 | 70.19 | 78.49 | 62.45 | 82.70 | 73.35 | 57.98 | 76.53 | 84.77 | 82.91 |
|            | C4       | 85.99 | 80.41 | 85.02 | 72.77 | 87.98 | 78.16 | 70.23 | 87.43 | 90.44 | 89.33 |
|            | C5       | 90.11 | 87.24 | 88.88 | 82.62 | 92.16 | 89.01 | 76.04 | 93.01 | 93.31 | 94.06 |
|            | C6       | 90.39 | 87.67 | 89.07 | 79.62 | 92.77 | 86.47 | 76.14 | 92.25 | 93.17 | 93.27 |
|            | C7       | 93.30 | 93.56 | 93.51 | 87.66 | 95.60 | 92.98 | 83.78 | 96.63 | **96.76** | **96.38** |

Table 3: Accuracy (%) comparison of existing approaches with our proposed setting using different classifiers
Effect of Analysis Window

| Classifier | Technique | Subjects |
|------------|-----------|----------|
| WA         | 11 12 13 14 15 16 17 18 19 20 | 94.63 97.41 96.09 97.33 96.94 98.04 97.6 97.26 97.6 98.2 |
| AG         | 88.36 89.91 88.24 87.57 92.89 89.56 87.43 88.16 88.81 91.59 |
| C1         | 95.95 97.97 96.8 97.94 97.84 98.52 98.22 97.83 98.47 98.44 |
| C2         | 87.32 89.90 82.84 90.48 89.14 90.80 83.95 94.32 91.40 92.76 78.94 |
| kNN        | C3         | 85.58 91.52 80.79 88.11 91.94 89.82 93.90 90.10 90.60 90.06 |
|            | C4         | 85.56 91.21 80.93 88.66 91.46 89.57 94.33 89.54 91.33 89.79 |
|            | C5         | 77.56 80.08 67.39 82.30 74.05 85.69 85.61 85.03 88.33 62.49 |
|            | C6         | 82.40 77.20 62.51 85.02 68.45 85.71 89.91 86.72 90.45 65.04 |
|            | C7         | 89.87 86.06 73.63 93.38 76.82 90.92 95.69 93.52 95.32 71.56 |
| WA         | 49.21 64.76 66.46 52.15 68.92 63.33 69.12 54.28 65.58 72.16 |
| AG         | 33.85 47.66 41.39 45.80 58.07 45.83 41.66 40.63 38.09 45.79 |
| C1         | 52.43 66.27 68.12 52.95 70.61 64.59 70.62 54.85 68.48 73.37 |
| C2         | 18.39 30.27 28.25 26.94 34.07 28.06 28.40 25.64 28.50 32.84 |
| NB         | C3         | 17.54 24.54 30.66 22.18 27.73 27.99 26.88 22.74 25.26 27.71 |
|            | C4         | 19.41 32.52 32.32 28.37 35.99 34.11 35.09 30.63 29.10 36.04 |
|            | C5         | 22.09 38.98 36.21 35.35 41.64 42.38 41.07 36.27 40.15 43.44 |
|            | C6         | 19.96 37.89 37.84 34.97 43.10 41.79 43.04 39.20 40.52 45.28 |
|            | C7         | 21.25 37.5 39.16 34.54 43.31 43.29 40.13 34.19 40.18 43.68 |
| WA         | 39.38 57.03 53.41 46.10 43.26 50.74 48.46 43.16 53.19 49.68 |
| AG         | 20.71 32.39 28.26 37.80 36.13 32.90 30.69 31.96 31.71 28.16 |
| C1         | 41.06 58.96 44.23 49.01 44.22 52.83 48.84 43.46 49.36 54.54 |
| C2         | 27.64 31.75 30.89 35.42 34.03 31.15 32.07 30.35 35.92 30.43 |
| DT         | C3         | 24.23 38.43 27.00 28.31 24.54 35.70 35.33 29.51 28.43 31.05 |
|            | C4         | 26.63 33.94 34.48 30.32 33.37 34.59 31.21 31.08 34.61 32.58 |
|            | C5         | 24.53 35.06 31.72 30.94 39.19 40.67 37.70 37.39 40.61 36.96 |
|            | C6         | 24.11 42.04 34.30 36.89 30.71 32.53 39.88 37.50 40.34 39.90 |
|            | C7         | 33.38 47.17 33.77 38.84 40.08 38.43 39.26 40.19 41.22 35.88 |
| WA         | 85.76 89.19 89.58 88.40 92.74 90.55 90.62 88.17 92.48 90.14 |
| AG         | 93.93 95.21 94.76 94.57 95.96 94.46 94.23 94.19 95.96 96.57 |
| C1         | 92.15 93.25 95.19 93.36 95.87 94.56 94.75 93.66 95.68 94.64 |
| C2         | 54.91 67.20 64.01 60.34 66.55 62.39 71.34 60.81 64.63 52.74 |
| SVM        | C3         | 55.08 75.00 72.06 64.87 73.78 75.90 78.22 69.60 74.08 75.55 |
|            | C4         | 66.35 83.70 81.98 73.19 82.49 81.42 85.88 75.61 81.75 80.32 |
|            | C5         | 74.98 87.24 86.80 81.07 88.70 87.37 89.59 82.28 86.28 85.15 |
|            | C6         | 76.07 88.30 87.68 79.16 89.05 85.96 89.25 81.62 88.05 84.97 |
|            | C7         | 83.58 90.93 94.03 87.15 92.52 92.15 93.17 87.16 91.49 91.43 |

Table 4: Accuracy (%) comparison of existing approaches with our proposed setting using different classifiers
### Table 5: Accuracy (%) comparison of existing approaches with our proposed setting using different classifiers

| Classifier | Technique | Subjects |
|------------|-----------|----------|
|            | WA        | 21       |
|            | AG        | 22       |
|            | kNN       | 23       |
|            | C1        | 24       |
|            | C2        | 25       |
|            | C3        | 26       |
|            | C4        | 27       |
|            | C5        | 28       |
|            | C6        | 29       |
|            | C7        | 30       |
| WA         | 96.19     | 97.33    |
| AG         | 88.54     | 88.74    |
| kNN        | 97.90     | 98.04    |
| C1         | 97.90     | 97.76    |
| C2         | 91.71     | 91.78    |
| C3         | 90.11     | 91.41    |
| C4         | 90.41     | 91.01    |
| C5         | 80.94     | 83.33    |
| C6         | 81.60     | 85.26    |
| C7         | 90.68     | 91.68    |
|            | WA        | 96.80    |
|            | AG        | 86.50    |
|            | kNN       | 96.14    |
| C1         | 97.85     | 96.34    |
| C2         | 95.21     | 94.30    |
| C3         | 90.04     | 90.34    |
| C4         | 89.36     | 89.34    |
| C5         | 84.04     | 84.09    |
| C6         | 86.71     | 86.84    |
| C7         | 91.21     | 91.66    |
|            | WA        | 96.81    |
|            | AG        | 96.42    |
|            | kNN       | 96.42    |
| C1         | 97.79     | 98.01    |
| C2         | 91.21     | 89.15    |
| C3         | 91.00     | 90.34    |
| C4         | 89.18     | 89.34    |
| C5         | 89.58     | 89.58    |
| C6         | 85.29     | 85.29    |
| C7         | 92.25     | 94.53    |
|            | WA        | 97.37    |
|            | AG        | 95.65    |
|            | kNN       | 96.81    |
| C1         | 97.97     | 98.06    |
| C2         | 91.21     | 89.15    |
| C3         | 91.00     | 90.34    |
| C4         | 89.18     | 89.34    |
| C5         | 89.58     | 89.58    |
| C6         | 85.29     | 85.29    |
| C7         | 92.25     | 94.53    |
|            | WA        | 96.81    |
|            | AG        | 96.42    |
|            | kNN       | 96.42    |
| C1         | 97.79     | 98.01    |
| C2         | 91.21     | 89.15    |
| C3         | 91.00     | 90.34    |
| C4         | 89.18     | 89.34    |
| C5         | 89.58     | 89.58    |
| C6         | 85.29     | 85.29    |
| C7         | 92.25     | 94.53    |
|            | WA        | 97.37    |
|            | AG        | 95.65    |
|            | kNN       | 96.81    |
| C1         | 97.97     | 98.06    |
| C2         | 91.21     | 89.15    |
| C3         | 91.00     | 90.34    |
| C4         | 89.18     | 89.34    |
| C5         | 89.58     | 89.58    |
| C6         | 85.29     | 85.29    |
| C7         | 92.25     | 94.53    |
### Table 6: Accuracy (%) comparison of existing approaches with our proposed setting using different classifiers

| Classifier | Subjects | WA | AG | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|------------|----------|----|----|----|----|----|----|----|----|----|
| kNN        | 13       | 96.50 | 85.20 | 98.11 | 88.82 | 89.20 | 88.95 | 83.96 | 84.80 | 92.60 |
|            | 31       | 97.57 | 89.65 | 97.87 | 92.69 | 92.98 | 93.16 | 84.09 | 84.65 | 91.83 |
|            | 32       | 98.08 | 89.58 | 98.47 | 95.20 | 95.75 | 95.53 | 87.21 | 87.80 | 92.10 |
|            | 33       | 98.04 | 90.04 | 98.74 | 95.20 | 95.75 | 93.24 | 89.07 | 89.10 | 93.59 |
|            | 34       | 93.43 | 56.50 | 85.97 | 86.66 | 82.67 | 83.93 | 80.40 | 81.51 | 88.57 |
|            | 35       | 96.07 | 89.22 | 98.57 | 93.19 | 92.23 | 89.33 | 82.88 | 81.78 | 89.50 |
|            | 36       | 97.90 | 89.06 | 97.10 | 94.23 | 93.24 | 92.30 | 88.76 | 87.27 | 93.71 |
|            | 37       | 96.73 | 87.22 | 98.08 | 88.67 | 89.05 | 93.25 | 84.50 | 87.33 | 84.90 |
|            | 38       | 95.43 | 88.86 | 96.73 | 90.95 | 89.99 | 93.22 | 83.71 | 85.35 | 85.31 |
|            | 39       | 97.34 | 88.86 | 95.43 | 93.25 | 93.20 | 93.23 | 84.90 | 85.35 | 83.81 |
|            | 40       | 97.34 | 88.86 | 97.34 | 93.25 | 93.20 | 93.23 | 84.90 | 85.35 | 83.81 |

### 6 Conclusion and Future Work

In this paper, we investigate the effect of the analysis window on the accuracy using the available sEMG dataset from the NinaPro database, which contains a variety of hand movements. Our results on different classifiers indicate that averaging out analysis window affects the classification accuracy (because vital information gets averaged out). Furthermore, we also investigate the effect of different combinations of features on classification accuracy. We find out that kNN classifier has an average accuracy of more than 95% with a particular configuration of features (C1). In the future, we will use data from amputated subjects and the data that involves more hand and wrist movements. Furthermore, we will apply different dimensionality reduction based techniques (e.g. singular
value decomposition) to reduce the dimensions of data while preserving valuable information. We will also try different methods to remove the noise from the data so that the overall accuracy can be further improved.

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