Physical Action Classification Based on Surface EMG Signals Analysis

Paridhi Arya (S20210020305), Pratik Agrawal (S20210020312), and Vaibhav Prajapati (S20210020328)

***Abstract*—With a rising population experiencing limb disabilities and gait disorders necessitating medical intervention, robot-assisted rehabilitation therapy stands as a promising avenue for their recovery and reintegration into daily life. An effective methodology involves utilizing EMG (Electromyography) signals to control supportive robotics, translating the biological motor intention into actionable information for the robot's controller. To achieve this, an accurate understanding of motor intention is imperative, demanding a pattern recognition-based framework. This report presents an enhanced classification framework by identifying pivotal features essential for driving the pattern recognition algorithm.**

***Index Terms*—EMG, Classification, Feature Extraction, Robot-Assisted Rehabilitation**

I. Introduction

A. Motivation

PHYSICAL disabilities pose significant challenges in modern society, arising from diverse causes such as aging-related issues, occupational injuries, trauma, stroke-induced disabilities, and amputations. These disabilities, whether partial or complete, greatly impact an individual's quality of life. Statistics reveal a substantial number of individuals affected by these conditions, with hundreds of thousands of people requiring prosthetic limbs or partial limb support annually.

Current treatment options for these disabilities are limited. Therapeutic rehabilitation stands as a viable approach for aiding partially disabled individuals in regaining functionality and enhancing their quality of life. Wearable robots have emerged as a promising avenue to augment the effectiveness of rehabilitation procedures. Studies suggest that robot-assisted therapy can significantly enhance motor skills, primarily due to increased therapeutic repetitions and heightened patient motivation facilitated by virtual reality and video gaming elements.

Moreover, wearable robotics can alleviate the challenges faced by individuals in performing manual tasks. Externally powered prosthetics or orthotic exoskeletons offer potential solutions to restore limb functionality to some extent for those with disabilities. A crucial aspect of these applications is developing a human-robot interface capable of interpreting user intentions to provide accurate and timely assistance.

In a healthy individual, the central nervous system communicates with muscle groups via motor neurons to execute intended motions. However, in individuals affected by amputations or stroke-induced disabilities, the bioelectrical signals may not effectively reach the muscles or elicit the necessary force for movement. An engineering solution involves utilizing EMG (Electromyography) sensors to capture myoelectric signals associated with muscle activity. By extracting relevant information from these signals, such as estimating joint force and decoding movement intentions, these signals can be relayed to controllers to generate the intended motion.

B. The Physical Actions Classification Problem

The primary focus of this assignment lies in harnessing the potential of machine learning algorithms, particularly KNN (K Nearest Neighbour), to analyze EMG signals and accurately classify physical actions. In essence, EMG signals represent the electrical activity linked to muscle recruitment through neuronal firings. Leveraging these signals to decode intended movements presents an opportunity to bridge the communication gap between the nervous system and muscles, offering a promising avenue for advancing rehabilitation and assistive technologies for individuals with physical disabilities.

Within the realm of machine learning, the utilization of EMG signals provides a unique opportunity to interpret and classify physical actions. The KNN algorithm, renowned for its simplicity and effectiveness in classification tasks, emerges as a significant component in this assignment. Through this machine-learning-centric approach, the goal is to contribute to the development of robust classification models that can effectively decode and differentiate between distinct physical actions based solely on EMG signal patterns.

II. Methodology

A. Dataset Description

The data set of interest is taken from the UCI Machine learning repository. The dataset consists of the EMG signals recorded using the Delsys EMG electrodes on S = 4 subjects while they performed C = 20 different physical activities of which 10 were aggressive and 10 were normal activities as listed in Table I.

Each subject repeats the physical action R = 15 times. There were 8 EMG electrodes placed on each subject, the first 4 on the biceps and triceps muscle groups of the upper limbs and the next 4 on the thighs and hamstring muscle groups of the lower limbs. Finally, each channel consists of approximately 10, 000 values. Hence, in this study, the total sample size becomes $P = 4 \times 20 \times 15 = 1200$.

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- Number of Instances: 10,000
- Number of Attributes: 8

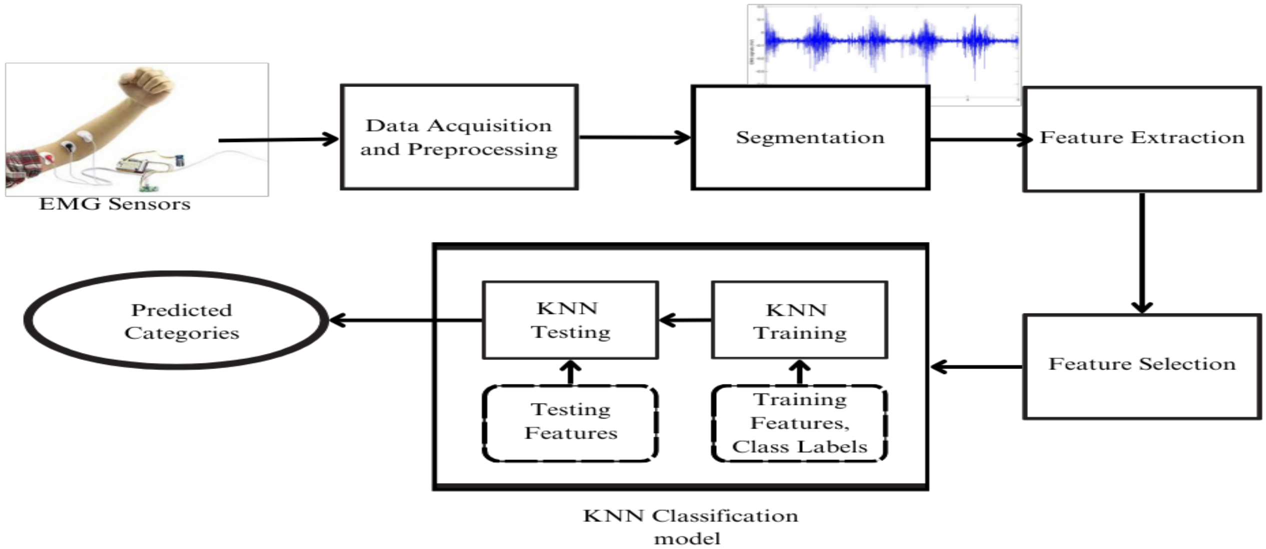

Fig. 1: Block Diagram of Physical Action Classification using KNN

TABLE I
PHYSICAL ACTION CATEGORIES AND CLASS LABELS

Label	Normal	Label	Aggressive
1	Bowing	11	Elbowing
2	Clapping	12	Frontkicking
3	Handshaking	13	Hammering
4	Hugging	14	Headering
5	Jumping	15	Kneeing
6	Running	16	Pulling
7	Seating	17	Punching
8	Standing	18	Pushing
9	Walking	19	Side-kicking
10	Waving	20	Slapping

- Attribute Information:
  Each file in the dataset contains in overall 8 columns, and is organised as follows:

Channel 1	R-Bicep
Channel 2	R-Tricep
Channel 3	L-Bicep
Channel 4	L-Tricep
Channel 5	R-Thigh
Channel 6	R-Hamstring
Channel 7	L-Thigh
Channel 8	L-Hamstring

TABLE II: Channels and their corresponding muscles

- Segment: A segment defines a body segment or limb.
  - Right arm (R-Arm)
  - Left arm (L-Arm)
  - Right leg (R-Leg)
  - Left leg (L-Leg)
- Channel: A channel corresponds to an electrode attached on a muscle.
- Muscle: A pair of muscles that corresponds to a segment.
  - R-Bic: right bicep (C1)
  - R-Tri: right tricep (C2)
  - L-Bic: left bicep (C3)
  - L-Tri: left tricep (C4)
  - R-Thi: right thigh (C5)
  - R-Ham: right hamstring (C6)
  - L-Thi: left thigh (C7)
  - L-Ham: left hamstring (C8)
- Number of Classes: 20
  The dataset consists of 10 normal and 10 aggressive physical actions.
  - Normal: Bowing, Clapping, Handshaking, Hugging, Jumping, Running, Seating, Standing, Walking, Waving
  - Aggressive: Elbowing, Frontkicking, Hamering, Headering, Kneeing, Pulling, Punching, Pushing, Sidekicking, Slapping

We consider a dataset X with P(= S × C × R) observation arrays or samples obtained from S subjects. This dataset has 4 distinct rows, corresponding to each subject. Thereafter, for each subject, it has data for 10 normal and 10 aggressive activities nested within it. For each of these activities, there are roughly 10,000 instances and for each of these instances, there are 8 channels.

Three male and one female subjects (age 25 to 30), who have experienced aggression in scenarios such as physical fighting, took part in the experiment. Throughout 20 individual experiments, each subject had to perform 10 normal and 10 aggressive activities. The ’Normal’ actions represent regular, non-aggressive movements, while the ’Aggressive’ actions simulate more forceful and intensive physical activities. Hence, the dataset is diverse, encompassing variations in

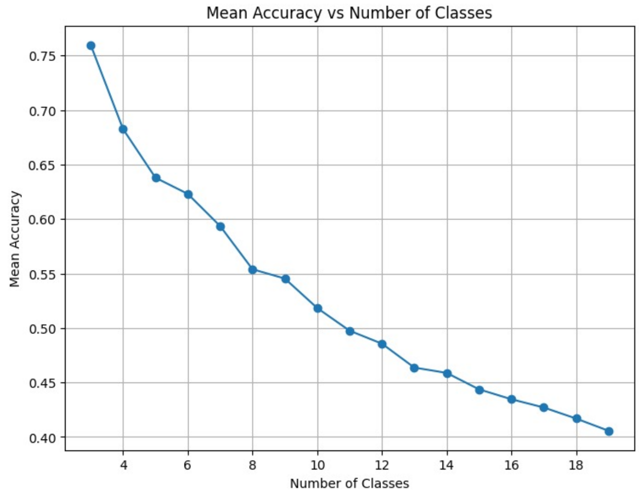

Fig. 2: Mean accuracy as a function of number of classes

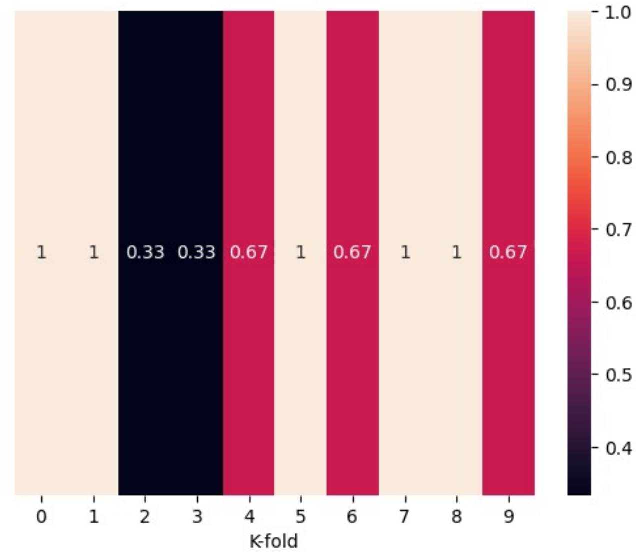

Fig. 3: Heatmap of Mean accuracy as a function of number of classes

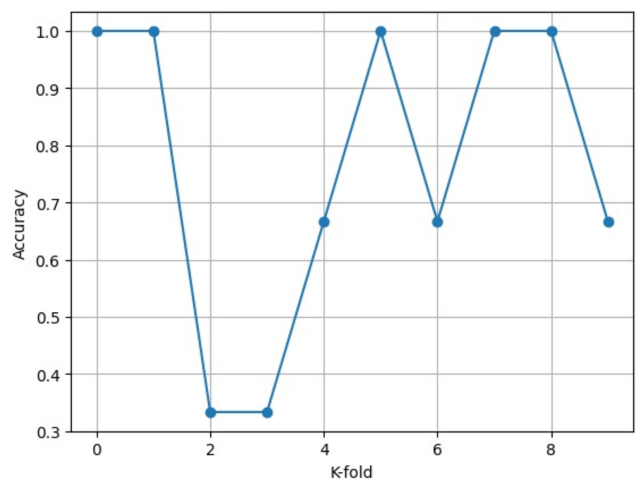

Fig. 4: Mean accuracy as a function of number of folds

subjects, actions, and conditions.

B. Data Pre-Processing

Data Pre-processing involves initially exploring the dataset structure to understand its organization and content. We determined the number of folders (4), subjects (4), and actions(20), gaining insights into the overall dataset size. Thereafter, we built a data preprocessing pipeline. This encompassed loading the EMG signals from the text files, removing noise with filtering techniques, and normalizing the signals to ensure uniformity among subjects and actions.

C. Feature extraction and visualization

The first step is the segmentation of the EMG signal in each channel with a non-overlapping and a sliding window length L, which is derived based on the sampling rate of the concerned EMG data. For each of the subjects, we divide the time series array into individual trials. There are 15 trials in each array. For each trial, we divide the signal into N_s number of segments of segments and extract mean and variance features for each of these segments. Thereafter, we concatenate these features from the N_s segments and concatenate these feature vectors from 8 channels into an ensemble of 8 x N_s x 2 features.

The first subset of features is computed from the sample statistics for each segment within a pattern. The mean value for the j-th segment is defined as

$$\mathrm{f}_t(j) = 1/N_w \sum_{l=1}^{N_w} s_j(l)$$

Similarly, the variance, skewness and kurtosis are computed. Finally, for a p-th pattern, the 4 features from each segment and M channels are grouped into the Time Domain Statistics feature vector.

D. Label Extraction

Next, we perform label extraction by concatenating the target vectors into a single vector from Normal and Aggressive activities.

E. Classification of pairs of classes and multiple classes

We then combine the inputs and outputs into a single array with 1200 samples with N_f features, where

N_f = no. of features x no. of segments (N_s) x no. of channels (M)

P = No. of subjects (S) x no. of classes (C) x no. of trials (R)

F. Analysis

For further analysis, we sample any two classes from the 20 classes at random and report the cross-validation classification performance. Thereafter, we repeat the sampling process for multiple classes ($2 \leq$ C $\leq$ 19), and determine the number of classes at which the cross-validation performance starts

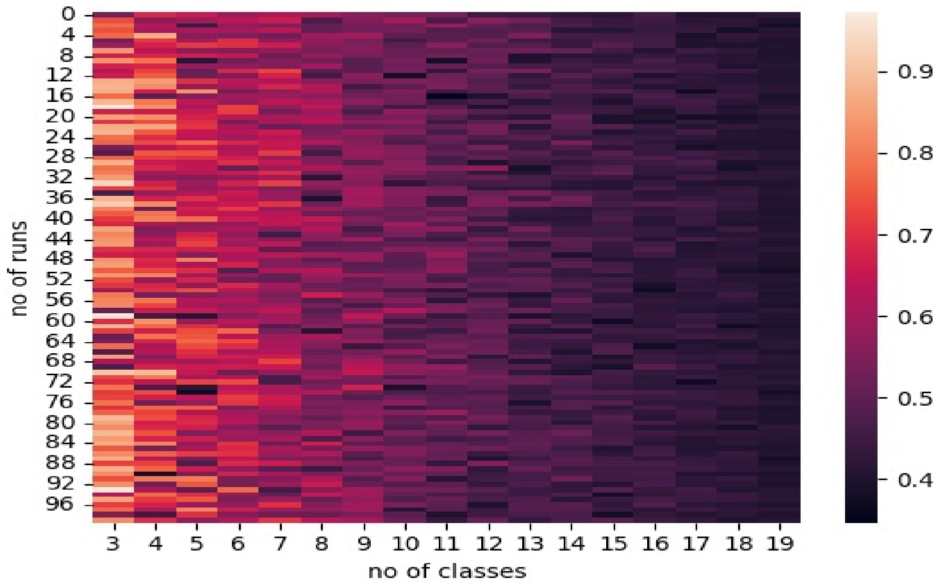

Fig. 5: Heatmap of Mean accuracy as a function of number of MC runs and number of classes

to degrade rapidly by generating a classification accuracy vs number of classes plot along with heatmaps. Further, we assess the mean accuracy as a function of the number of classes and Monte Carlo (MC) runs.

III. Case Studies

In this physical actions classification task, we perform binary as well as multi-class classification.

A. *Binary classification analysis (C = 2)*

Initially, using K-Fold cross-validation with a KNN classifier, the code computes the overall accuracy in a binary classification setting. For binary classification, the mean accuracy is the highest (Fig 2.), at about 77%. We can also assess accuracy as a function of folds and note that 0, 1, 5, 7, and 8 fold cross-validation gives us the best results in terms of mean accuracy. This can be visualized in the form of a line plot, as in Fig. 4, or as a heatmap, as in Fig. 3.

B. *Multi-classification analysis ($3 \leq C \leq 19$)*

Subsequently, we explore the effect of the number of classes on classification accuracy. The analysis reveals a consistent trend: as the number of classes increases from 2 to 19, the mean accuracy diminishes. This decline illustrates the increasing complexity of distinguishing among multiple classes, indicating the inherent challenge in accurately classifying data into numerous categories. Consequently, we can visualize using a heatmap how the number of classes and the number of Monte Carlo runs influences the accuracy of classification models, showcasing the greater difficulty in achieving accurate predictions as the number of distinct classes expands.

IV. Conclusion

Using the features derived from 8 channels of the surface EMG data, we performed binary class as well as multi-category classification framework in this study to classify the physical actions. Features were extracted from various modalities, including the statistical features in the time domain, such as mean and variance. A subset of these features was found to be relevant for the physical action classification using the sequential forward selection algorithm. In terms of channel relevance, the EMG data from the upper limbs has greater significance in physical action classification. In terms of channel relevance, the EMG data from the upper limbs has greater significance in physical action classification. Based on the selected features, the average classification performance metrics for KNN were evaluated as a function of number of classes ($2 \leq C \leq 19$) and of Monte Carlo runs.

Appendix

Code for Physical Action Classification ('main.ipynb' in linked Github Repository)