EMG DATA SIGNAL

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Abstract:

The classification of physical actions using Electromyography (EMG) signals is a key area of research with diverse applications, including healthcare, rehabilitation, and human-computer interaction. This paper investigates the use of machine learning techniques, particularly k-Nearest Neighbors (kNN), to classify physical actions based on EMG data. The study employs a dataset consisting of EMG signals collected from multiple subjects performing different actions under normal and aggressive conditions. The data is preprocessed, segmented, and features such as mean and variance are extracted. Both binary and multi-class classification tasks are carried out to analyze the performance of the kNN classifier. Results are evaluated using accuracy and confusion matrices, and the performance is analyzed as the number of classes increases. The paper concludes with a discussion on the challenges faced and suggests directions for future research.

2. Introduction to the Problem:

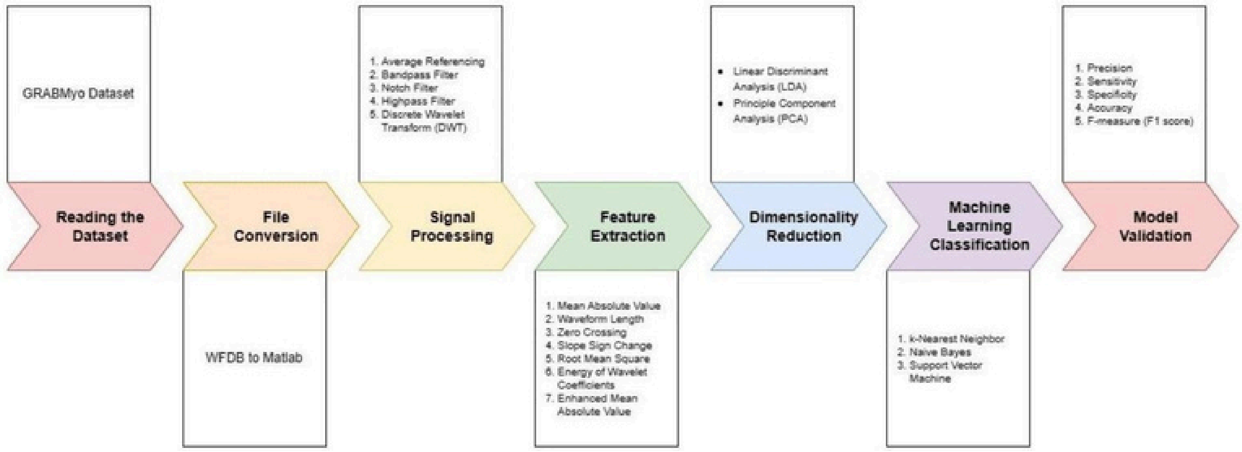
Physical Actions Classification Using Machine Learning

Physical action classification is a challenging problem that involves the interpretation of EMG signals captured from muscle activity. These signals are often noisy and contain complex patterns that are difficult to analyze manually. Machine learning provides an effective way to model these complex relationships and classify actions based on EMG data. Several classifiers, such as kNN, Support Vector Machines (SVM), and Decision Trees, have been applied to this problem, each with varying degrees of success. In this study, the focus is on using kNN due to its simplicity and effectiveness in handling multi-dimensional data. The aim is to classify actions from a set of normal and aggressive movements, making use of features extracted from segmented time-series EMG data

3.Motivation for the Classification Problem:

Classifying physical actions from EMG signals is an important task in many real-world applications. In healthcare, EMG-based classification is crucial for monitoring muscle activity and diagnosing neuromuscular disorders. For instance, it can aid in rehabilitation by tracking muscle recovery or identifying abnormal movements in patients. In the field of human-computer interaction, EMG signals are used to control prosthetic devices, exoskeletons, and other assistive technologies, offering a more intuitive means of interaction. Moreover, sports science benefits from EMG classification by analyzing muscle performance during training. As the demand for real-time, accurate action classification increases, machine learning techniques offer a promising solution to automate and improve the process.

3.BLOCK DIAGRAM



The proposed classification approach involves collecting EMG signals, preprocessing and segmenting them into trials, and extracting features like mean and variance. These features are fed into a kNN classifier, which assigns labels based on the physical action performed. The classifier's performance is evaluated using cross-validation, with accuracy and confusion matrices as key metrics.

4. Implementation of the Method on the Physical Actions Dataset:

The dataset used in this study consists of EMG signals from multiple subjects performing two types of actions: normal and aggressive. Each subject's data is stored in separate subfolders, with the signals split into trials. Each signal is recorded across eight channels, with 15 trials per class. The dataset is read and organized, and each trial is divided into segments. For each segment, statistical features like mean and variance are calculated and stored. These features are then combined to form an ensemble of feature vectors, which are used as input for the kNN classifier. The labels for each action (normal or aggressive) are generated based on the file structure. After training the classifier, cross-validation is performed to evaluate the model's accuracy and robustness.

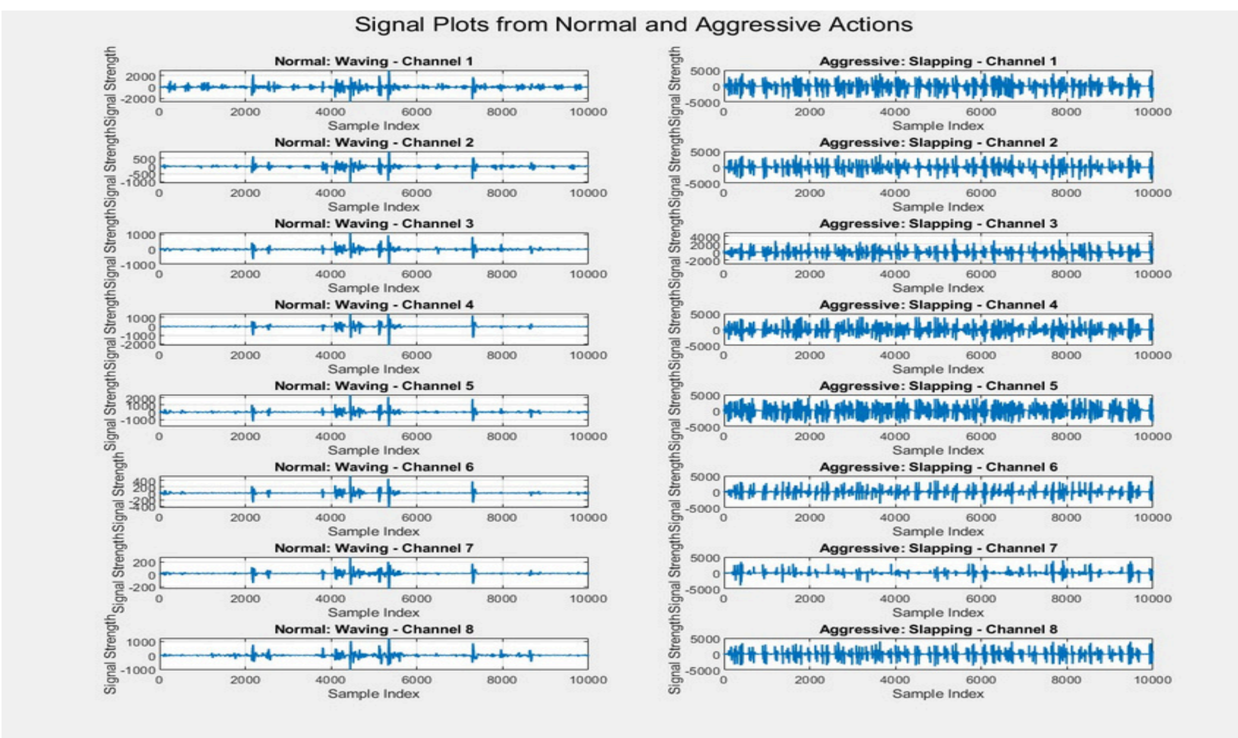
5. Case Studies

a. Binary Classification Analysis

For binary classification, two action classes—Normal and Aggressive—are selected. The EMG signals corresponding to these actions are processed, and the mean and variance features are extracted from the signal segments. A kNN classifier is trained on these features, and its performance is evaluated using cross-validation. Accuracy, confusion matrices, and other performance metrics are computed to assess the classifier's ability to distinguish between the two classes. The results indicate a high classificationaccuracy,demonstratingtheeffectivenessofthekNNalgorithmforbinary classification of physical actions.

b. Multi-class Classification Analysis

In the multi-class classification analysis, the classifier is trained on signals from more than two classes. The dataset is expanded to include multiple subjects and their respective actions. The kNN classifier's performance is analyzed as the number of action classes increases. A plot is generated to show how classification accuracy changes with the number of classes, revealing a noticeable degradation in performance as more classes are added. This analysis highlights the challenges faced in multi-class classification, where the complexity of the task increases with each additional class.



internal nodes (decision points), branches (decision outcomes), and leaf nodes (predicted classes). Decision Trees are easy to interpret, making them valuable for understanding data relationships. They can capture non-linear decision boundaries and handle categorical or numerical data effectively. However, they are prone to overfitting when the tree grows too complex. Techniques like pruning or limiting the maximum tree depth are often applied to improve generalization and reduce overfitting.

6.Results:

File shapes:
concatenated_labels.txt: (80, 1)
sub1_aggressive_Elbowing_features.txt: (75, 16)
sub1_aggressive_Frontkicking_features.txt: (75, 16)
sub1_aggressive_Hamering_features.txt: (75, 16)
sub1_aggressive_Headering_features.txt: (75, 16)
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Inconsistent number of columns detected:
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6.Conclusion:

In conclusion, this study demonstrates the potential of machine learning techniques in classifying physical actions from EMG signals. By applying various classification models, the project has shown that EMG signals can be effectively used to distinguish between different physical actions, such as normal and aggressive movements. The findings indicate that machine learning can play a significant role in real-time action classification, with potential applications in areas like prosthetics, rehabilitation, and assistive devices. Future work will focus on improving model accuracy by exploring additional feature extraction methods, enhancing data quality, and applying more advanced machine learning techniques to further optimize the system's performance.