Combined EEG and EMG Signal for Controlling Prosthetic Hand

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Abstract: In this research paper, we presentfa brain-controlled bionic hand capable of executing precise finger movements. Our investigation spans five key domains. Firstly, we explore Brain- Computer Interface (BCI) technology, encompassing non-invasive and partially invasive methods, and highlight its potential in augmenting cognitive and sensory-motor functions. Secondly, we delve into human brain physiology, emphasizing the role of the primary motor cortex and the significance of brainwave patterns, particularly Mu waves, in controlling motor functions. Thirdly, we examine Electromyography (EMG) as a means to monitor skeletal muscle activity, assess muscle health, and understand muscle function, detailing signal acquisition, processing, and filtering techniques.

The fourth domain covers Data Acquisition and Processing, focusing on the utilization of the Bio Radio system for capturing brainwave signals. We discuss signal filtering, exportation, and the integration of the software development kit (SDK) and introduce the International 10-20 system for electrode placement. Lastly, we explore the realm of Robotic Hand Movements, stressing the importance of anthropomorphism and dexterity in robotic hand design. Actuator selection and control mechanisms are elaborated upon, featuring a prototype equipped with five servo motors controlled by alpha brainwave levels. The study also divides into feature extractionftechniques and machine learning algorithms for the classification of brain signals associated with finger movements, with a strong commitment to ethical research practices to ensure originality and avoid plagiarism. In conclusion, our research introduces a ground- breaking brain-controlled bionic hand with the potential to revolutionize human-machine interaction and prosthetic design, with promising applications in medical prosthetic and advanced robotics.

Introduction

Brain-controlled bionic hands represent a remarkable con- vergence of neuroscience, engineering, and artificial intelligence, holding immense promise in the domains of medical prosthetics and robotics. These multifaceted systems aim to emulate the intricate intricacies and dexterity of the human hand, offering life-altering possibilities for individuals with limb loss or motor impairments. In this paper, we embark on an extensive exploration of brain-controlled bionic hands, delving into the intricate processes and technologies that underpin their functionality.

At the heart of these state-of-the-art prosthetic systems resides Brain-Computer Interface (BCI) technology, which serves as the pivotal conduit between the human brain and external robotic devices. BCIs have undergone significant evolution, encompassing non-invasive modalities like electroencephalography (EEG) and invasive methods, each tailored to specific user requirements and challenges. Non-invasive BCIs, notably EEG-based systems, have garnered substantial attention due to their safety and user-friendliness. By capturing and decoding electroencephalographic signals originating from neural activity, EEG-based BCIs empower users to manipulate robotic hands through their cognitive intent, endowing them with an unprecedented sense of control and autonomy.

Intricately intertwined with the evolution of brain-controlled bionic hands is the pursuit of anthropomorphism and dexterity. Anthropomorphism entails the capacity to bestow robotic end- effectors with the capability to mimic the nuanced characteristics of the human hand. This quality assumes paramount significance in enabling these robotic arms to efficaciously navigate environments designed for human use, interact seamlessly with tools and objects designed ergonomically for human hands, and facilitate intuitive teleoperation through interfaces mirroring human limb behavior. This notion attains its zenith in the realm of humanoid robotics, where the robot's subsystem must seamlessly emulate human-like behavior across a spectrum of tasks.

The mechanical synthesis phase, a pivotal juncture in the design process, plays an instrumental role in endowing a robotic hand with the coveted attributes of anthropomorphism and dexterity. This phase closely delineates the topology of the core functional elements: fingers, palms, and wrists. The mechanical synthesis proffers comprehensive geometric specifications, material selection, and actuation mechanisms crucial for the holistic development of a robotic arm. The critical choice of actuators, fundamental to efficient finger mechanics, mandates a judicious evaluation of parameters such as actuator count, dimensions, torque capacity, speed, power consumption, and cost-effectiveness. Electrically powered motors, a commonly embraced actuation modality, are adept at directly imparting motion to finger joint articulations. Alternatively, tendon-driven systems, bevel mechanisms, or precision gear trains may be custom-engineered to suit specific application requirements.

Distinguishing our approach is the incorporation of brain- wave data, specifically attention and meditation levels discerned from alpha brainwave patterns, within the control framework. This pioneering integration begets the ability for users to steer the robotic hand via neural intent, thus heralding a paradigm shift towards cognitive-driven control in the realm of prosthetics.

To facilitate the translation of brainwave data into action- able control directives, a crucial intermediary step is feature extraction. This essential process is tasked with retaining real-time responsiveness, despite the intrinsic time-intensive nature of comprehensive feature extraction. The mitigation strategy here involves the segmentation of signals utilizing predefined windows, which could be either disjoint or overlapping. For this project, the choice leans towards discontinuous windowing due to its inherent computational efficiency. Several feature extraction methodologies come into play, with a pronounced emphasis on time-domain features to ensure computational expediency. Techniques such as Mean Absolute Value (MAV), Autoregressive Coefficients, and Integrated EMG (IEMG) as- sume pivotal roles in transforming brainwave data into tangible control signals.

Literature Review

The field of brain-controlled robotics has witnessed remarkable progress in recent years, with a focus on Brain-Computer Interface (BCI) technologies, robot arm movement, and their integration. This literature review provides a comprehensive overview of key research endeavors and breakthroughs in this burgeoning domain.

BCI and Brainwave Acquisition

In the realm of BCI technology, Jeong et al. [1] have made significant contributions with their brain-controlled robot arm system. Their research explores upper-limb movement imagery, modularizing the experimental architecture into Brain-Machine Interface (BMI), network, and control components. The study validated the feasibilityfof EEG-based robot arm control for high-level tasks in multi-dimensional space. Similarly, Amali Ranifand Umamakeswari [2] pioneered the development of an EEG-based brain-controlled wheelchair using NeuroSky technology. This innovation offers portability and wearability, revolutionizing the mobility of paraplegics.

Jimenez Moreno and RodrÃŋguez AlemÃąn [3] delved into BCI applications by focusing on the control of a mobile robot using EEG signals captured by the Emotiv EPOC device. Their work highlighted the potential of Emotiv software and SDK for remote robot control. Svejda et al. [4] explored the utilization of complex EEG signals in BCI systems, emphasizing the need for robust single-unit recordings to enhance performance.

Robot Arm Movement

Prosthetic limb development has also seen notable advancements. Dunai, Novak, and Espert [9] presented a novel prosthetic arm design that bridges the gap between basic prosthetic hooks and expensive robotic hands. Their innovative approach incorporates mechanical concepts such as hydraulics, pneumatics, and unique thumb rolling motion. Ganguly [10] conducted theoretical analysis for a bionic arm, focusing on converting brain signals into mechanical energy to facilitate arm movement.

Yoosuf and Ahmed [11] offered insights into the replication of major human hand functions in bionic hands. They categorized prosthetic arms based on the level of amputation and highlighted the significance of myoelectric upper limb technologies.

EEG-Based Brain Wave Control

Nakirekanti et al. [6] developed a brain wave-controlled robot using EEG signals processed in MATLAB. Their work underscores the importance of detecting brain signals and translating them into control commands, particularly beneficial for individuals with neuromuscular disorders. Hong et al. [13]

introduced an EEG-based intelligent 3D printed prosthetic arm, which utilizes alpha wave classification through Support Vector Machine (SVM) to enable amputees to control arm movements.

In summary, these studies represent a comprehensive exploration of brain-controlled robotics. They cover critical aspects of BCI technology, robot arm movement, and EEG-based control systems. These findings provide valuable insights into the development of brain-controlled robotic arms, revolutionizing various domains including healthcare and prosthetics. This literature review sets the stage for our research, synthesizing the wealth of knowledge available in this exciting and evolving field.

Methodology

There are 4 processes in the project. Firstly, the dataset recording offthe participant. Secondly, preprocess the signal to reduce the noise. Then, extract the featurefneeded in this project from the dataset. Lastly, thefclassify the dataset into 120 left forearm movement. These will do for both EMG and EEG dataset.

EEG Dataset

EEG Data Recording:

EEG signals are captured using the BioRadio EEG device. Participants wear the device with conduction paste applied to the electrodes to ensure good signal quality.

EEG Signal Pre-Processing:

- Median Filter: Raw EEG signals are filtered using a median filter to remove noise such as DC offset and unwanted brain activity and muscle movements.

- Band-Pass Filter: A band-pass filter with cutofffrequencies of 0.16 Hz and 45 Hz is applied to further filter the noise in the raw signal.

- Discrete Wavelet Transform (DWT): The EEG signal is decomposed into "approximate" and "detail" signals using DWT with Quadrature Mirror Filters. This decomposition helps analyze the frequency components of the signal.

Feature Extraction:

- Fast Fourier Transform (FFT): FFT is used tofconvert the EEG signal from the time domain to the frequency domain. This allows for visualization of the alpha wave, which is important for hand movement detection.

Dataset Collection:

Data from four participants are collected, and the focus is on collecting data related to alpha waves in the frequency domain during finger movements.

Classification Method:

- Support Vector Machines (SVM): SVM is initially used to create a binaryfclassifier. The Gaussian kernel function is chosen due to its effectiveness in high dimensions.

- Deep Learning Algorithms: Due to the lack of information on 120 finger movements, deep learning algorithms are explored. This includes:

  - Recurrent Neural Networks (RNNs): Long Short-Term Memory (LSTM) networks are designed to handle temporal data with sequential structures.

- Convolutional Neural Networks (CNNs): CNNs are used to capture spatio-temporal features in the EEG data. They can analyze how electrode activations change over time concerning specific movements.

EMG Dataset

1. EMG Data Acquisition:

EMG data is collected using the EMG sensors.

Participants are instructed to place EMG electrodes on their right arm.

2. EMG Signal Pre-Processing:

Pre-processing is crucial for handling complex biomedical signals like EMG.

Various techniques, including time-domain features, spectral analysis, zero crossing, turns counting,froot mean square, integral offRMS, and wavelet analysis, can be used for noise reduction and signal enhancement.

In this study, the "Mean Absolute Value" (MAV) method is used for time-domain feature extraction. MAV involves taking the absolute values of individual EMG data points, windowing the data, and computing the average values within each window.

The choice of window length (L) is important for MAV, and different window lengths are experimented with to optimize classification accuracy.

3. Integration with EEG Data:

The extracted features from EMG data are likely combined with EEG data to create a comprehensive dataset that includes both types of signals.

4. Classification Methods:

Classification methods are applied to the combined EEG and EMG dataset to recognize specific hand movements.

These classification methods are trained to identify different classes of hand movements based on the acquired signals.

5. Data Source for Model Building:

Due to the unavailability of real-time data from the BioRadio, an external EMG dataset with labeled gestures is used to build and test the classification model.

The external dataset contains signals categorized into ten classes corresponding to individual or combined finger movements.

6. Data Transmission:

MATLAB is used on a laptop to acquire real-time raw brainwave signals from the BioRadio. These raw brainwave signals are processed in real-time and transmitted wirelessly to a microcontroller using RF (Radio Frequency) modules. The microcontroller interprets the brainwave data, particularly attention and meditation levels, to control the robotic arm. The robotic arm comprises five servo motors responsible for finger movements, and the microcontroller uses the acquired brainwave data to control these motors.

Predefined levels of attention and meditation are used as triggers for specific actions in the robotic arm.

Results

A. K-Nearest Neighbors Classifier (KNN)

KNN algorithm was implementedfwith various parameters and trained with 10-fold cross-validation tofobtain the accuracy values as below.

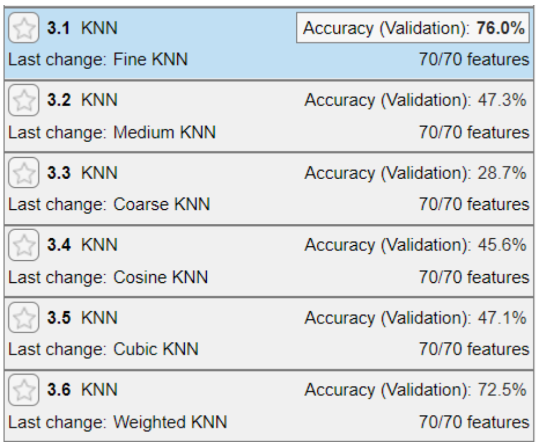

Figure 1: KNN accuracy chart

The highest accuracyFcan be observed when classifier parameters are set to,

1. Number of neighbor/s - 1
2. Distance metric - Euclidean
3. Distance weight - Equal

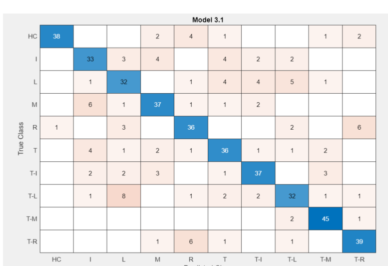

Figure 2: KNN confusion matrix

After selecting the optimalfparameters, the classifier was trained again with extractedffeatures from principal component analysis. PCAFwas implemented several times toFkeep the various number of numericFfeatures at several classification sessions.

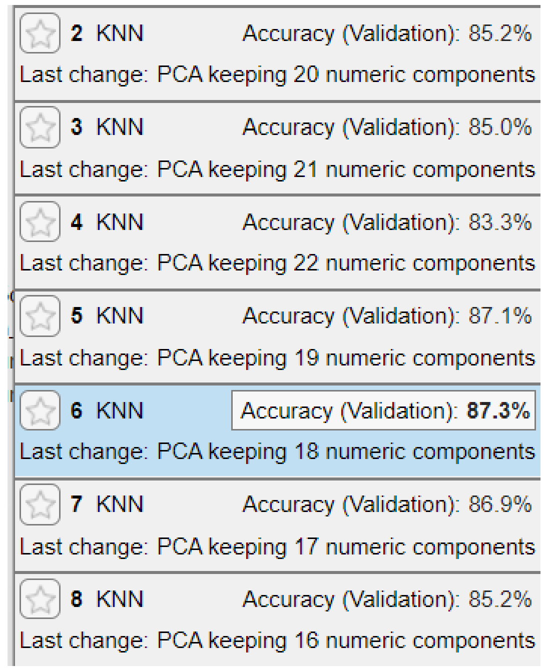

Figure 3: KNN implementation with PCA

The highest classification accuracy wasfobtained when PCA was used tofextract 18 numeric features. A confusionfmatrix was obtained for the trainingfsession with the highest accuracy.

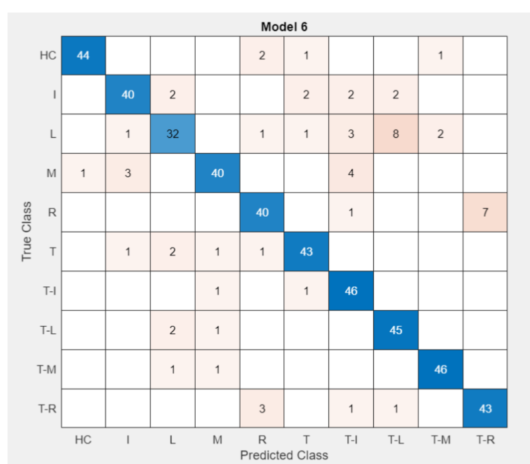

Figure 4: KNN confusion matrix with PCA

Support Vector Machine Classifier (SVM)

SVM algorithm was implemented onfthe dataset with various parameters and 5-fold cross-validation.

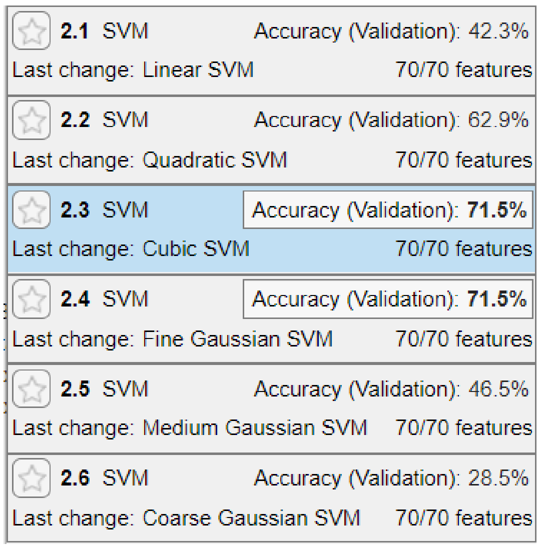

Figure 5: SVM Implementation

The highest accuracyFcan be observed when classifier parametersfare set to,

1. Kernel function-cubic
2. Kernel scale mode-auto
3. Box constraint level / Highest penalty - 1
4. Multi-class method - one vs one

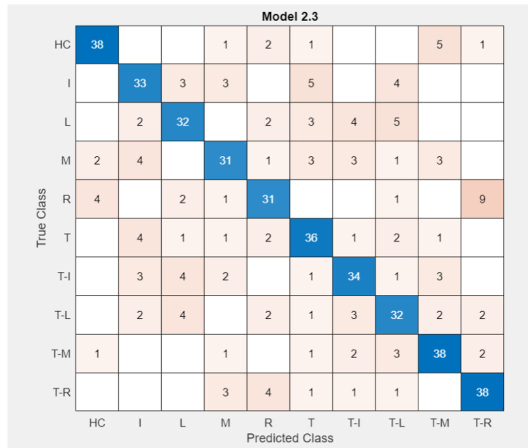

Figure 6: SVM confusion matrix

After selecting the best settings, the classifier was trained again with extracted features from principal component analysis. PCA was implemented numerous times to maintain varied quantities of numeric features during several categorization sessions. But it required more processing power. Therefore, we couldn't attain accuracy using PCA for SVM implementation.

Other conventional classification techniques such as Decision tree algorithms, Naive Bayes, and ensemble learning were also applied on the dataset. Almost majority of them failed to create adequate accuracy levels with the exception being ensemble learning algorithm with an accuracy of 75% using the following parameters,

1. Ensemble method - bagged trees
2. Learner type - decision tree
3. Maximum number of splits - 599
4. Number of learners - 30

Artificial Neural Networks (ANN)-feedforward neural network

ANNs were constructed using the TensorFlow machine learning framework with Keras deep-learning library. The network comprised of an input layer, output layer, and 5 hidden layers. Dropout with a 0.1 chance of output retention was included on first 4 layers as a regularization parameter to reduce overfitting. Any number bigger or lower than 0.1 was demonstrated to degrade the accuracy levels of the algorithm. Input layer and buried layers comprised of 70 neurons apiece. Determining the number of neurons for each layer was done via trial and error. Other optimized settings include

1. Activationffunction - Rectified linear unit (ReLU)
2. Activation function (output layer) - SoftMax (normalizefexponential function)
3. Optimizer -Adamf(stochastic gradient decent)
4. Loss function - Categorical cross entropy
5. Epochs (cycles through dataset) - 1500

Application of PCA substantially lowered classifier performance therefore not regarded helpful. With these data, it may be stated that the optimized KNN classifier obtains the greatest accuracy level of 87.3% while the optimized feedforward ANN classifier is at second place with 84.17% accuracy and optimized SVM earned 71.5% accuracy. But these results are not effective for real-time classification since the latency duration between muscle contraction and categorization is unsatisfactory.

Conclusion

In this study, the primary goal was to develop a real-time pattern recognition model for controlling a prosthetic hand using both EEG and EMG data. However, due to limitations with real-time data capture and the unavailability of EEG sensors in Sri Lanka, the focus shifted to using EMG sensors. Despite challenges in finding precise EMG sensors, the study employed ECG sensors as an alternative, although they were not particularly accurate.

The primary emphasis of the project became the machine learning component. EMG data was segmented based on designated time windows for real-time recognition, and feature extraction techniques were applied. Multiple classifiers were tested, with the best-performing one being KNN with a 500ms window length, achieving an 87.3% accuracy rate for each classification.

While there were obstacles and limitations, the study's results suggest success in creating a real-time model for prosthetic hand control. The designed model can be implemented in real-time on a suggested prosthetic controller or any compatible device, offering promise for future developments in this field.

Future Development

In the future development plan, the focus is on addressing limitations encountered during the project. The acquisition of reliable sensors, including a precise EMG sensor and an EEG headset, is a primary goal to improve data quality for model training. Furthermore, the plan involves increasing the number of EMG channels to provide richer data sources, ultimately enhancing the model's ability to accurately recognize hand gestures. Feature optimization is another key aspect, with plans to refine the methodology by selecting meaningful features, eliminating less important ones, and streamlining calculations, all of which can contribute to improved model performance. Testing the model on a desktop workstation ensures its functionality in a controlled environment before transitioning to practical applications. Lastly, fine-tuning the model for use in a prosthetic controller is crucial, ensuring its effectiveness in real-world scenarios, ultimately advancing the goal of creating an accurate and efficient prosthetic hand control system.

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