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[Surface EMG Based Hand Gesture Signal Classification Using CNN for Control of Software Robot]

Submitted
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Under the Guidance of

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DECLARATION

I/We declare that the project work contained in this report is original and it has been done by me under the guidance of my project guide.

Name:

Date: **Signature of the Student**

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CERTIFICATE

This is to certify that (Student Name) bearing (Regd. No.:) has satisfactorily completed Mini Project Entitled in partial fulfillment of the requirements as prescribed by University for VIIth semester, Bachelor of Technology in "Electrical, Electronics and Communication Engineering" and submitted this report during the academic year 2024-2025.

[Signature of the Guide] **[Signature of HOD**

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Chapter 1: Introduction:

1.1 Overview of the problem statement:

It pertains to a challenge where one must build a model that recognizes hand gestures with the help of surface emg signals, which will enable the control of a robot designed on software. sEmg and these are sensors used to measure the electrical muscle response from muscles tightened, and this response needs to be categorized by the model into hand gestures in accordance with which the robot is controlled. The problems faced in this challenge are: making sure that accurate recognition is achieved despite variation in users of the model, processing such signals in real-time, reducing excessive retraining as much as possible, and still being able to work effectively when the position of sensors or the degree of fatigue of the muscle's changes. The aim is to achieve an efficient and user-friendly control system through the use of advanced signal processing and deep learning techniques.

1.2 Objectives and Goals:

Objectives:

- To develop a hand gesture recognition model using surface EMG signals to control a software designed robot.

Goals:

- Design an accurate hand gesture recognition model using automatic feature extraction and classification technique like CNN with attention mechanism.

- Develop a software robot whose moment will be controlled using developed hand gesture recognition model.

Additional Goals:

- To create a dataset using surface EMG sensor.
- Analysis of hand gesture model performance with the proposed method.

Chapter 2: Literature Review:

2.1: Hand Gesture Recognition based on Surface Electromyography using Convolutional Neural Network with Transfer Learning Method: Published in 2021, this study was authored by X. Chan, et al.

Link: Research paper 1

2.2: Hand Gesture Recognition using SEMG Signals Based on CNN: Published in 2021, this study was authored by Li Bo, et al

Link: Research paper 2

2.3: Hand Gesture Recognition Using Compact CNN Via Surface Electromyography Signals: Published in 2020, this study was authored by Lin Chen, et al

Link: Research paper 3

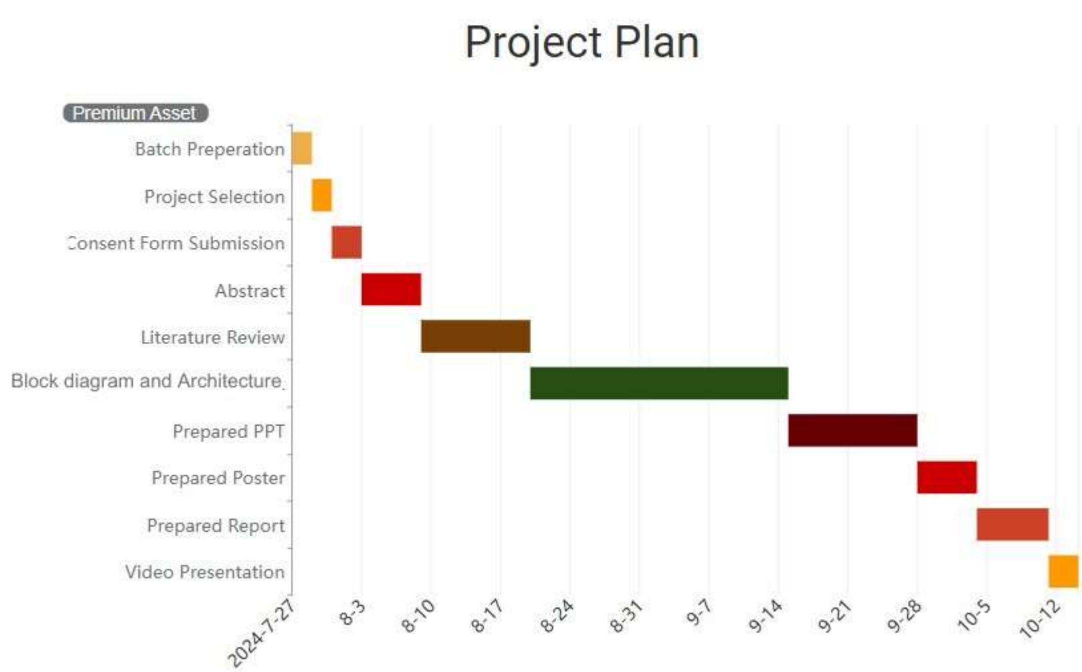
2.4: Hardware and Software Design and Implementation of Surface-EMG-Based Gesture Recognition and Control System Published in 2024, this study was authored by Z. Zhang, et al

Link: Research paper 4

Chapter 3: Strategic Analysis and Problem Definition:

3.1 SWOT ANALYSIS

3.2 Project Plan - GANTT Chart



3.3 Refinement of problem statement

Original Problem Statement: Surface EMG Based Hand Gesture Signal Classification Using CNN for Control of Software Robot.

Refined Problem Statement: To design an EMG-based hand gesture recognition system using CNN, aimed at controlling a software robot with high precision and minimal user training.

Chapter 4: Methodology

4.1 Description of the approach

1. Data Collection: -

- Collected sEMG signals for 30 hand gestures (source set) and three target sets (new users, new gestures, public dataset). - Used high-density sEMG arrays on the forearm and upper arm from 28 participants.

2. Data Preprocessing: -

- Segmented sEMG signals, filtered noise, normalized data, and reshaped it into image-like formats for CNN input.

3. CNN-based Feature Extraction: -

- Designed a CNN (Source Convent) to learn gesture features from the source set. This network was trained and used as the base model for transfer learning.

4. Transfer Learning:

- Two target networks:
- CNN-only: Transferred CNN layers, fine-tuned FC layers.

- CNN+LSTM: Used CNN for spatial and LSTM for temporal features, trained LSTM layers on target sets.
- Made a comparison between Transfer Learning (TL) and Non-TL (trained from scratch).

5. Training and Evaluation:

- Indicated full-batch learning to train target networks on new datasets. Analyzed gesture recognition accuracy and training time. - Out of the obtained results, two-way ANOVA was employed to evaluate TL versus Non-TL results.

4.2 Tools and techniques utilized:

Software Tools:

1. Data Acquisition:

- Surface EMG Sensors: Used to study muscle behavior during various hand gestures.

- NinaPro Dataset: An openly available dataset for training and testing purposes.

2. Data Preparation:

- Processing stages involved in classification includes removing noise, scaling and segmentation of sEMG signals.

3. Machine Learning:

- CNNs (Convolutional Neural Networks): Used for automatic feature extraction as well as for the gesture classification task.

- Transfer Learning: For enhancing accuracy and saving on training time.

4. Model Development and Test:

- Integration of a Software Robot: The detected gestures were used to command the robotic device.

- Carrying out real time testing for precision as well as response speed.

5. Evaluation:

- Assessed the accuracy of classification accomplished and also attempted other placements and situations of the sensors.

Design considerations:

- **Precision and Reliability:** Strived for high precision and dependability in performance across varying users and settings.
- **Real-time Control:** Provided immediate control in the operation of software robotics and professional device limbs for the user.
- **Data Preprocessing:** Filtration, normalization, and feature extraction were utilized to obtain clean sEMG signals.
- **Scalability and Generalization:** Achieved Generalization to other datasets with minimal retraining by means of transfer learning.

- **User-friendly Setup:** Allowed for straightforward attachment of sensors with less user modification needed.
- **Hardware Efficiency:** Focused on low computational overhead because of the need for real time performance.
- **Testing:** Conducted in field-testing under different test scenarios.

Chapter 5: Implementation:

5.1 Description of how the project was executed:

The project was executed in two phases, each aimed at improving the hand gesture recognition model using surface electromyography (sEMG) signals for controlling a software-designed robot.

Phase 1:

- **Objective**: The primary aim was to build the convolutional neural network model using surface electromyography (sEMG) data in order to classify and recognize hand gestures.
- **Implementation**: sEMG signals for five hand gestures were collected using the Myo Armband. To enable automatic feature learning, a convolutional neural network with three convolutional layers was developed to operate on the raw sEMG signals and classify into different gestures.
- **Achievements**: The model was able to achieve 70% of accuracy. Nevertheless, it was not able to recognize hand gestures that were too close to each other, such as a pinch and point.
- **Challenges**: The model was sensitive to the placement of electrodes and there was a latency in gesture recognition that was aimed to be performed in real time which caused a lag in controlling.

Phase 2:

Objective: It was decided to further optimize the accuracy and robustness of the CNN model by incorporating an attention mechanism.

Implementation: An attention layer was appended to the CNN and targeted at important parts of the sEMG signals for improvement in the gesture detection. The dataset was also expanded and augmented in order to perverse the model, while hyperparameters proved to be adjusted to achieve the desired performance.

Achievements: Thanks to this adjustment, the accuracy of the model reached 88%, with an improved ability to differentiate between gestures that are very similar. Moreover, classification latency was also lessened, thereby enhancing the control of the robot in real-time.

Challenges: The complexity of the model was unnecessarily escalated by the attention mechanism as it now demanded more computational resources and processing powers.

5.2 Challenges faced and solutions implemented:

Difficulty in Differentiating Similar Gestures:
Challenge: The CNN model struggled to distinguish between gestures that were very similar, such as pinch and point, leading to lower classification accuracy for certain hand gestures.
Solution: An attention mechanism was added to the CNN, allowing the model to focus on the most critical features of the sEMG signals. This improved the model's ability to distinguish between similar gestures.
Delayed Response in Real-Time Control:

Challenge: The initial model had a delay in recognizing gestures, which impacted the real-time control of the software robot.

Solution: By tuning the model's hyperparameters and optimizing the architecture, the classification speed was improved, reducing latency and enhancing the real-time control experience.

Increased Model Complexity:

Challenge: Adding an attention mechanism increased the complexity of the model, requiring more computational resources and slowing down the processing speed.

Solution: Although the model complexity increased, the team focused on balancing performance and resource efficiency, with plans for future optimizations to reduce processing demands without sacrificing accuracy

Chapter 6: Results

6.1 outcomes:

Improved Gesture Recognition Accuracy:

- The initial CNN model achieved a 70% accuracy rate but struggled with distinguishing similar gestures. After implementing the attention mechanism and tuning hyperparameters, the accuracy improved significantly to 88%.
- The attention layer helped the model focus on critical features in the sEMG signals, improving its ability to differentiate between gestures, even those that were similar (e.g., pinch vs. point).

Enhanced Real-Time Control:

- The classification latency was reduced, allowing for quicker response times during real-time control of the robot. This improvement enabled more seamless interactions between the user's hand gestures and the software robot's movements.

Increased Robustness:

- The model became less dependent on precise electrode placement due to dataset augmentation. This allowed the system to function accurately despite minor variations in sensor placement, making it more user-friendly and reliable.
- **Model Complexity and Resource Demand**:
- While the model's performance improved, the addition of the attention mechanism increased its complexity. This required more computational power and resources, which could be a limitation for deployment in low-power devices.

6.2 Interpretation of results:

- **Improved Accuracy**: The model's accuracy increased from 70% to 88% with the attention mechanism, helping it better distinguish between similar gestures like pinch and point.
- **Better Real-Time Control**: Reduced latency improved real-time response, allowing for smoother control of the software robot.
- **Increased Robustness**: The model became less dependent on precise electrode placement, handling variations better due to dataset augmentation.
- **Increased Complexity**: While accuracy and responsiveness improved, the model’s complexity and resource demands grew, which may limit use in low-power devices

6.3 Comparison with existing literature or technologies:

Chapter 7: Conclusion:

We have shown the construction of an accurate hand gesture recognition model using surface EMG signals with CNN incorporating the attention mechanism for automatic feature extraction and classification. This ability of the model to pay attention to the parts of the EMG signals most relevant to its decision not only increases precision and reliability of gesture recognition but also minimizes the need to do extensive manual feature engineering, hence creating a much more efficient and scalable solution to this particular problem.

Chapter 8: Future Work

Future work will be on the hardware design to implement control of a software-designed robot. More experiments with more sensors such as accelerometers to achieve better precision and the extension of the model to identify a larger variety of gestures would further improve system functionality. Testing the system under real-world conditions for long-term usability and building a generalized model for multiple users would be of great value as next steps.

Chapter 9: Team Progress and Movement

Dataset creation using sEMG sensors.

Development of the CNN-based classification model.

Integration of gesture recognition with software robot control.

Individual Contribution :

Avula Veera Siva Reddy:

- Data acquisition and pre-processing.

Boya Rajesh:

- CNN model design and implementation.

Bhanu Siva Sai Kumar M:

- Integration and testing of gesture recognition with robot control

Chapter 10 Reference:

Xiang Chen Member, IEEE, Yu Li, Ruochen Hu,Xu Zhang , Member, IEEE, and Xun Chen, Member, IEEE **Hand Gesture Recognition based onSurfaceElectromyography using Convolutional Neural Network with Transfer Learning Method** Research paper 1

Li Bo, Yang Banghua , Gao Shouwei , LinFeng Yan, Haodong Zhuang,Wen Wang **Hand Gesture Recognition using sEMG Signals Based on CNN** **Research paper 2**

Lin Chen , Jianting Fu , Yuheng Wu , Haochen Li , and Bin Zheng **, Hand Gesture Recognition Using Compact CNN Via Surface Electromyography Signals** **Research paper 3**

Zhongpeng Zhang , Tuanjun Han , Chaojun Huang and Chunjiang Shuai **Hardware and Software Design and Implementation of Surface-EMG-Based Gesture Recognition and Control System** Research paper 4