

CSCE 585: Real-Time EMG-Based Hand Gesture Recognition using SVM

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Contents

| | |
|-------------------------------|---|
| Introduction | 2 |
| 1 Problem Statement | 2 |
| 2 Technical Approach | 2 |
| 3 Evaluation..... | 3 |
| 4 Related Work | 4 |
| 5 References..... | 4 |

Introduction

Electromyography (EMG) provides a non-invasive means of measuring muscle activity and has applications in prosthetics, rehabilitation, and human-computer interaction. Gesture recognition using EMG signals allows intuitive control of devices and supports accessibility. However, real-time EMG classification poses challenges due to signal variability, noise, and the need for responsive, low-latency systems. This project proposes a machine learning pipeline leveraging Support Vector Machines (SVM) to classify EMG-based hand gestures in real time, while monitoring system performance through latency and throughput metrics.

1 Problem Statement

The problem is to design a reliable, real-time EMG-based hand gesture recognition system that achieves both high accuracy and low latency.

- **Dataset:** The project will use EMG recordings of hand gestures collected from publicly available datasets or generated via standard EMG acquisition hardware. These datasets typically include multi-channel EMG signals with labeled gesture classes.
- **Expected Results:**
 - Accurate classification of gestures from EMG signals using SVM.
 - Demonstration of real-time responsiveness by monitoring latency and throughput.
 - Insights into trade-offs between accuracy and system speed in biomedical signal processing.

2 Technical Approach

The proposed system will be built around an SVM classifier, with the following

pipeline:

- **Data Preprocessing:** Noise filtering, normalization, and segmentation of raw EMG signals.
- **Feature Extraction:** Extraction of features such as Root Mean Square (RMS), waveform length, and time-domain statistics.
- **Classification:** Training an SVM classifier on extracted features for multi-class gesture recognition.
- **System Monitoring:** Integration of latency and throughput metrics to evaluate performance in real time.

Rationale for SVM:

- Effective for small to medium-sized datasets with high-dimensional feature spaces.
- Robust to noise and well-suited for biomedical signals.
- Provides strong performance with relatively low computational cost compared to deep learning methods.

3 Evaluation

Metrics:

- AUROC, AUPRC
- Sensitivity, specificity, and calibration

Comparisons:

- ROC and PR curves against baselines
- Feature importance vs. traditional scoring system variables
- Statistical tests for model comparison

Expected Deliverables:

- Comparative analysis plots
- Feature attribution results
- A performance benchmark against existing clinical scores

4 Related Work

Previous studies have demonstrated the feasibility of EMG-based gesture recognition using machine learning models such as SVMs, random forests, and neural networks. While deep learning approaches achieve high accuracy, they often require significant computational resources, making them less suitable for real-time deployment. SVM-based methods strike a balance between accuracy, interpretability, and efficiency. This project builds on prior research by explicitly incorporating a latency and throughput monitor, ensuring the system is not only accurate but also practical for real-time applications.

5 References

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