Digital Signal Processing

Muscle Fatigue Detection using EMG signals

Abstract

Muscle fatigue, characterized by a decline in muscle performance over time, has significant implications in fields such as sports science, rehabilitation, and ergonomics. This project presents an efficient system for detecting muscle fatigue using surface Electromyography (sEMG) signals. The methodology encompasses data acquisition, signal preprocessing, feature extraction, and classification to determine fatigue states.This project highlights the use of affordable hardware and advanced signal processing for practical applications in rehabilitation, performance monitoring, and biomedical research. Future improvements could include real-time analysis and machine learning for more accurate and dynamic classification.

1 Introduction

Muscle fatigue is a condition characterized by a decline in a muscle's ability to generate force over time, which often occurs due to prolonged activity or stress. Detecting muscle fatigue is crucial in fields such as sports science, physical rehabilitation, ergonomics, and medical diagnostics. One effective method for monitoring muscle activity is through Electromyography (EMG), which records the electrical signals produced by muscles during contraction.

This project focuses on developing a cost-effective and reliable system to detect muscle fatigue using EMG signals. The system integrates both hardware and software components to collect, process, and analyze muscle activity data. The **Muscle BioAmp Biscuit sensor** is used to acquire raw EMG signals from bicep muscles, and the **Arduino Uno** is employed for signal digitization. The digitized data is then transferred to **MATLAB**, where Digital Signal Processing (DSP) techniques are applied to filter noise and extract meaningful features.

The signal processing involves two key steps:

1. **Preprocessing**: Removing noise using bandpass and notch filters.

2. **Feature Extraction**: Extracting both time-domain features (Root Mean Square, Mean Absolute Value) and frequency-domain features (Mean Frequency, Median Frequency) to analyze muscle behavior under fatigue.

The system uses these features to classify the muscle as **fatigued** or **non-fatigued**, with results visualized through signal plots and classification charts. By combining low-cost hardware with advanced signal analysis techniques, this project demonstrates the feasibility of real-time muscle fatigue detection. The system has potential applications in **monitoring athlete performance**, **rehabilitation therapy**, and **workplace ergonomics**.

Future work aims to integrate real-time monitoring and machine learning algorithms to improve accuracy and scalability. This project represents a step toward accessible and efficient biomedical signal analysis systems.

2 Literature survey

The reviewed studies emphasize the importance of Electromyography (EMG) systems in detecting muscle fatigue, showcasing diverse approaches to signal acquisition, processing, and classification. The study by Syed Faiz Ahmed et al. highlights the use of surface EMG sensors to monitor the Flexor Carpi Radialis (FCR) muscle, utilizing Support Vector Machines (SVM) and Linear Discriminant Analysis (LDA) for classification. Key features like Mean Absolute Value (MAV) and Root Mean Square (RMS) are extracted after filtering the signals to differentiate between fatigued and non-fatigued states. Bunseng Chan et al. focus on developing a portable, non-invasive EMG system, addressing challenges like noise and user discomfort. Their system integrates reusable electrodes, wireless data transmission, and classifiers such as K-Nearest Neighbor (KNN) and SVM, making it suitable for clinical applications like rehabilitation and real-time monitoring. Abdulhamit Subasi and M. Kemal Kiymik, on the other hand, employ advanced techniques like Short-Time Fourier Transform (STFT), Wigner–Ville Distribution (WVD), Continuous Wavelet Transform (CWT), and Independent Component Analysis (ICA) to analyze non-stationary EMG signals. They achieve over 90

3 Methodology

This explains the systematic approach followed to detect muscle fatigue using EMG signals. The methodology is divided into several stages, encompassing hardware setup, data acquisition, signal preprocessing, feature extraction, and classification.

3.1 Hardware and Software Setup

The project combines hardware and software components to achieve real-time muscle fatigue detection. The main components are as follows:

1. Hardware:

Muscle BioAmp Biscuit: A compact and low-cost EMG sensor used to capture muscle activity.

Arduino Uno: A microcontroller board that performs analog-to-digital conversion (ADC) of the EMG signal and transmits it to the computer via serial communication.

Electrodes: Surface electrodes are placed on the bicep muscle to capture EMG signals.

2. Software:

MATLAB: Used for signal preprocessing, feature extraction, and classification.

Arduino IDE: Used for programming the Arduino to read analog signals and transmit them to the laptop.

3.2 Data Acquisition

The EMG signals were recorded using the following procedure:

1. Surface electrodes were placed on the bicep muscle with proper skin preparation to ensure good contact.

2. The Muscle BioAmp Biscuit captured the raw EMG signal and transmitted it as an analog voltage.

3. The Arduino Mega, programmed with a sampling frequency of 1 kHz, performed ADC and sent the digitized EMG data to the laptop via a USB connection.

3.3 Signal Preprocessing

Preprocessing was performed to enhance the signal quality by removing noise and artifacts. The steps included:

1. Bandpass Filtering: A bandpass filter (20–500 Hz) was applied to remove irrelevant low-frequency motion artifacts and high-frequency noise.

2. Normalization: The filtered signal was normalized to a specific range for better comparison and feature extraction.

3.4 Feature Extraction

Feature extraction was conducted to derive meaningful characteristics from the preprocessed EMG signals. Both time-domain and frequency-domain features were computed:

1. Time-Domain Features:

Root Mean Square (RMS): Indicates the signal's power and correlates with muscle contraction levels.

Mean Absolute Value (MAV): Reflects the average muscle activity over a segment.

2. Frequency-Domain Features:

Fast Fourier Transform (FFT): Applied to convert the signal from the time domain to the frequency domain.

Mean Frequency (MNF): Represents the weighted average frequency of the power spectrum.

Median Frequency (MDF): Frequency at which the cumulative power equals half the total power.

These features were extracted from 200 ms non-overlapping signal segments to capture real-time variations in muscle activity.

3.5 Classification

The extracted features were used to classify the muscle state as fatigued or non-fatigued. A simple rule-based approach was employed:

1. RMS thresholds were defined to identify muscle contraction intensity.

2. MNF and MDF thresholds were set to detect frequency shifts typically associated with muscle fatigue.

3. Segments exceeding predefined thresholds were classified as fatigued, while others were labeled as non-fatigued.

3.6 System Workflow

The overall workflow of the project is shown in Figure **??**. It includes the following steps:

1. Data acquisition from the bicep muscles using hardware components.

2. Preprocessing the signal to remove noise and artifacts.
3. Extracting time-domain and frequency-domain features.
4. Classifying the muscle state and displaying the results.

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