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Real-time Control Applications Using Rapid Modeling Based on Surface Electromyography

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Introduction

The background of this study is based on the extensive application of surface electromyography (sEMG) in the fields of prosthetic control, rehabilitation training, and human-computer interaction. However, traditional sEMG modeling methods are often difficult to meet the requirements of real-time control due to data complexity and computation time limitations. With the rapid development of deep learning technology, especially the significant progress of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in sEMG signal analysis and hand motion recognition, this study explores how to use these advanced deep learning models to improve the real-time classification performance of sEMG signals, and how to achieve real-time control on resource-constrained devices by optimizing model design.

Research objectives

This study aims to propose a rapid modeling method based on surface electromyography (sEMG) for real-time control of finger movements. By designing sEMG datasets, extracting transient features, and applying deep learning algorithms such as Vision Transformer and ConvNext, this method effectively reduces the modeling time and improves the classification accuracy. Our goal is to optimize the classification accuracy and real-time performance of finger movements, making them suitable for a variety of real-time interactive systems, especially in the field of assistive devices and medical rehabilitation.

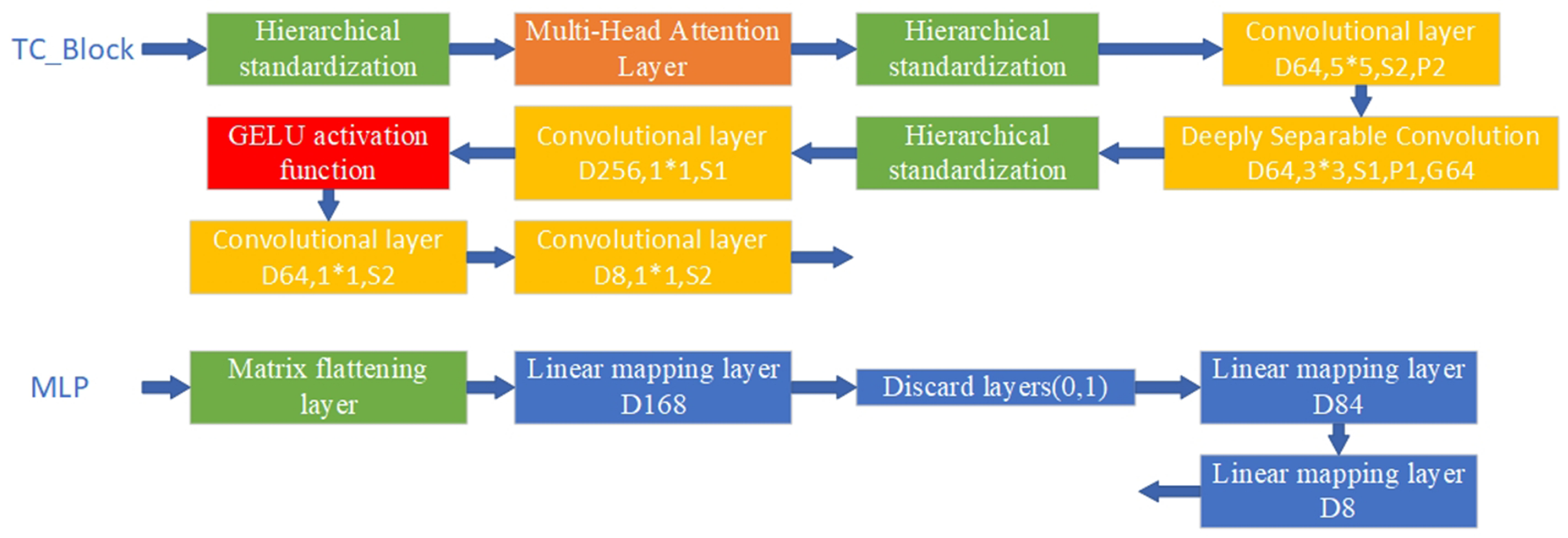
Methods

(1) Feature extraction

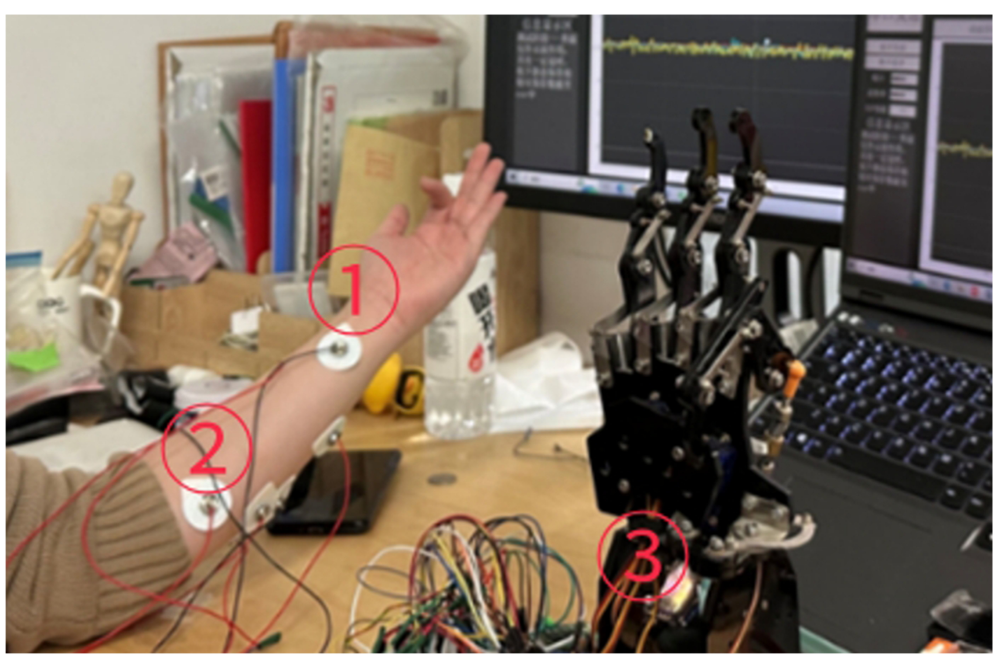
$$RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(sEMG(k))^2} \qquad WL = \sum_{k=1}^{N-1}|sEMG(k+1) - sEMG(k)|$$

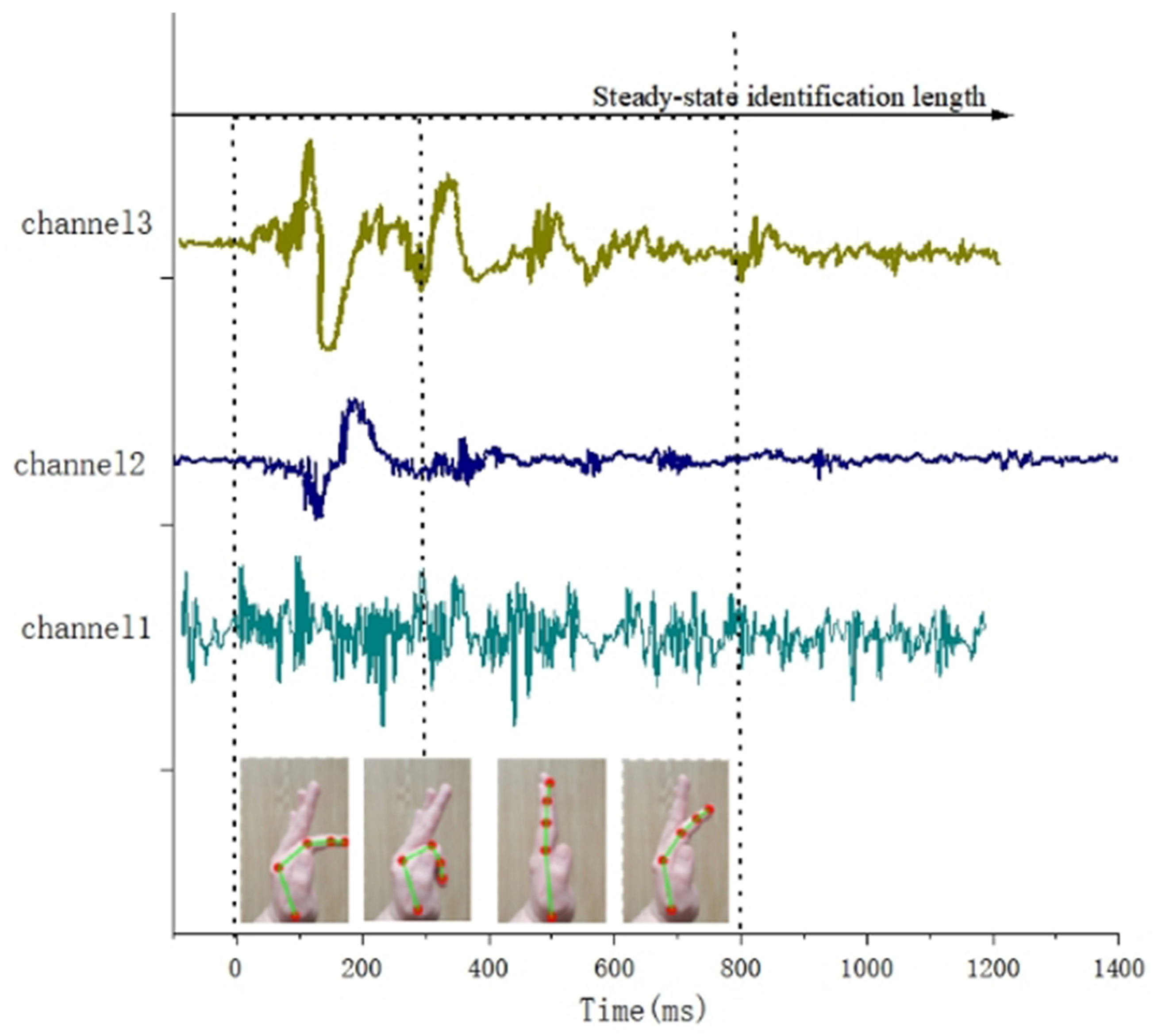
$$y = \frac{\sum_{i=1}^{Nl}|RMS_{i+1}(sEMG^{T}{}_{i+1}) - RMS_i(sEMG^{T}{}_{i})|}{Nl+1}, \quad Nl = T-1, \quad T = 8,16,32,$$

(2) The instantaneous feature extraction module and MLP are composed



(3) Experimental validation





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