GLOBAL RESEARCH IMMERSION PROGRAM FOR YOUNG SCIENTISTS

Grips

Network to measure arm stiffness through EMG signals

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INTRODUCTION

The analysis and interpretation of electromyography (EMG) signals have gained significant attention in recent years due to their potential applications in biomedical engineering, rehabilitation, and human-computer interaction. One of the key challenges in this domain is to accurately derive biomechanical properties, such as stiffness, from EMG signals. Traditional approaches for estimating muscle stiffness from EMG data often involve complex biomechanical models that require extensive domain knowledge and assumptions. However, these models can be limited by their sensitivity to individual variability and the inherent non-linearity of muscle behavior. With the advent of deep learning, new opportunities have emerged to develop data-driven methods that can learn direct mappings from EMG signals to stiffness values without the need for explicit biomechanical modeling.

In this work, we propose two approach based on CNNs and transformer network for the estimation of muscle stiffness from EMG signals. This study compares a CNN-based model and a transformer-based model for this task. The transformer model, in particular, excels at capturing inter-channel relationships across the six EMG channels, allowing for more precise stiffness estimation without relying on handcrafted features or explicit biomechanical assumptions.

OBJECTIVE

The main contributions of this work are as follows:

1. We introduce a novel application of transformer networks in the domain of EMG-based biomechanical signal processing.
2. We design a robust training framework that efficiently handles the variability and noise present in EMG data, leading to accurate stiffness estimations.
3. We validate the proposed model on a benchmark dataset and demonstrate its superior performance compared to traditional methods.

DATA

Data Collection

We conducted a comprehensive data collection process involving ten human subjects with diverse characteristics. The subjects were selected to represent a range of ages and body types, ensuring that the dataset captured a wide variety of physiological conditions and muscle behaviors.

Each subject participated in two data collection sessions. The first session involved recording EMG signals under a controlled physical state. One week later, the same subjects were invited back for a second session, where their EMG signals were recorded again under different physical conditions.

Dataset Description

The dataset includes 72 combined stiffness feature labels, each representing a specific biomechanical property derived from the EMG signals.

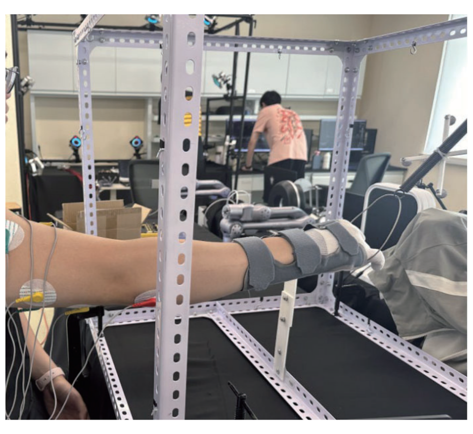


Fig. 1. Setting for EMG signal acquisition

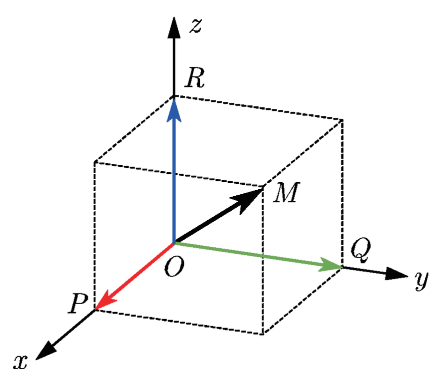


Fig. 2. The coordinate system for EMG signal acquisition

METHODOLOGY

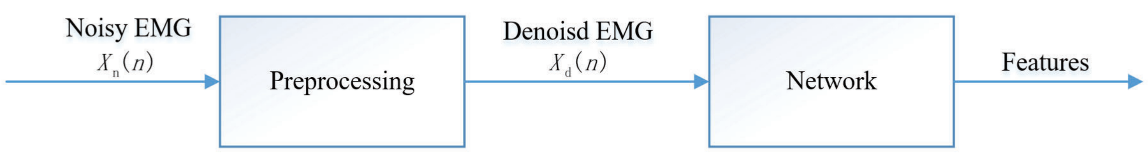


Fig. 3. Common structure of EMG analysis

1. Data Preprocessing

The raw EMG signals typically contain noise and artifacts that can interfere with accurate signal interpretation. To address this, we first preprocess the EMG signals using wavelet transform, which allows for the decomposition of the EMG signals into different frequency components. In our approach, we apply discrete wavelet transform (DWT) to the EMG data, which enables us to decompose the signal into approximation and detail coefficients at multiple levels. The approximation coefficients represent the low-frequency components of the signal, while the detail coefficients capture the high-frequency components. By selecting the appropriate wavelet function and decomposition level, we can effectively filter out noise and retain the relevant information needed for subsequent analysis.

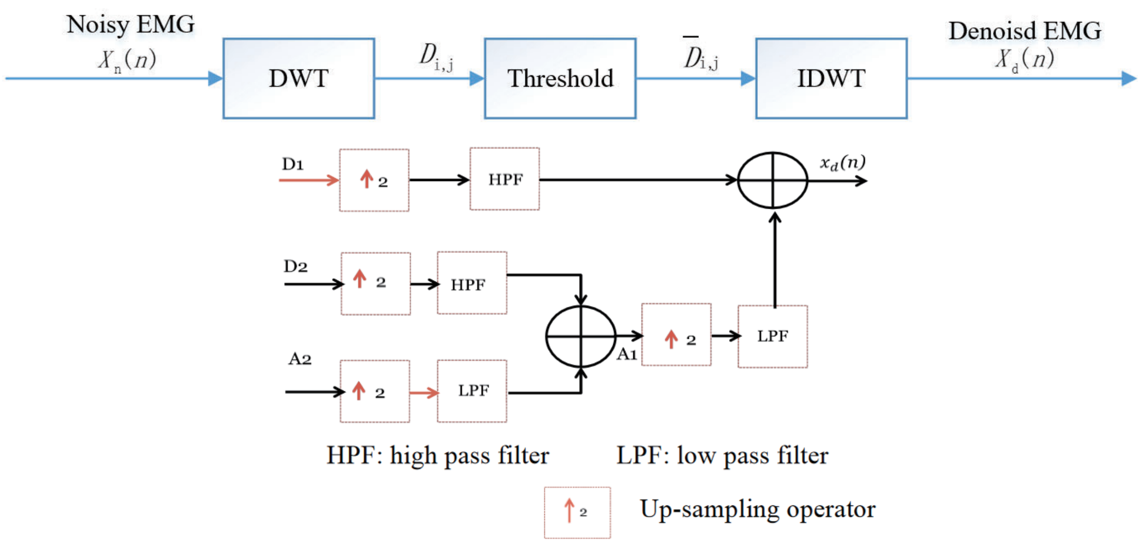


Fig. 4. Evaluation diagram with IDWT

2. Network Architecture

Our proposed network architecture in two separate ways. We first approach through CNNs and then follows Transformer models to capture both local features and long-range dependencies in the EMG signals. The architecture is designed to map the preprocessed EMG signals directly to stiffness values.

CNNs vs. Transformer

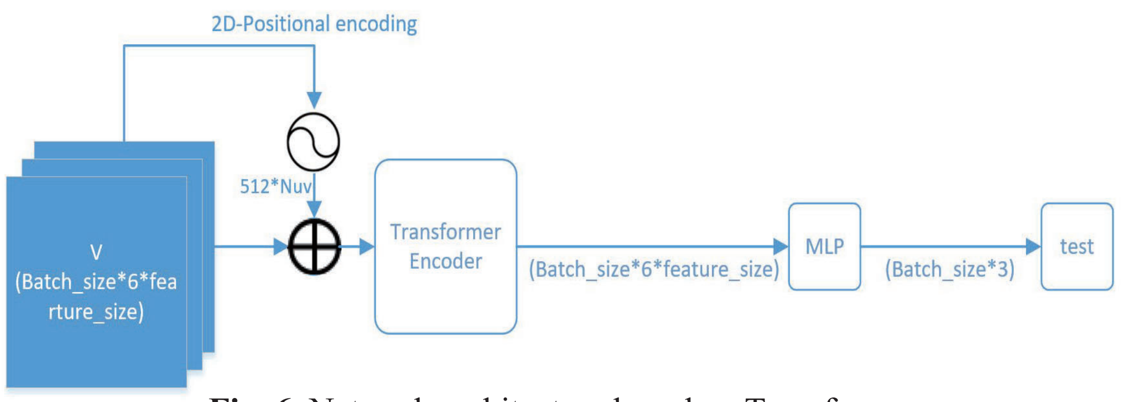


Fig. 6. Network architecture based on Transformer

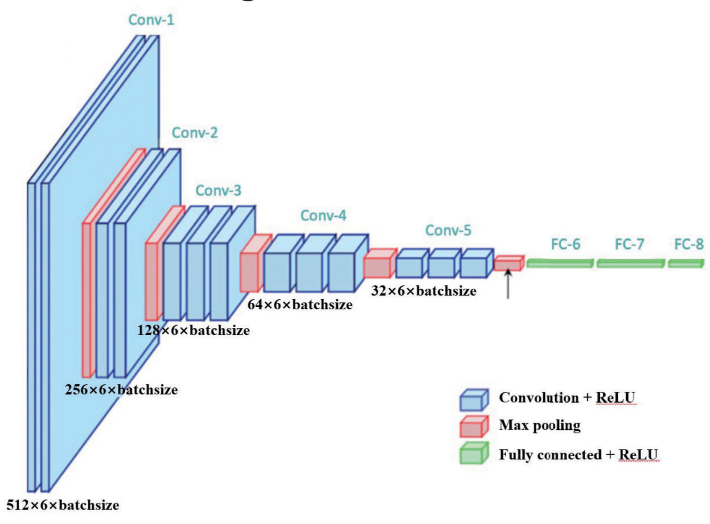


Fig. 7. Network architecture based on CNNs

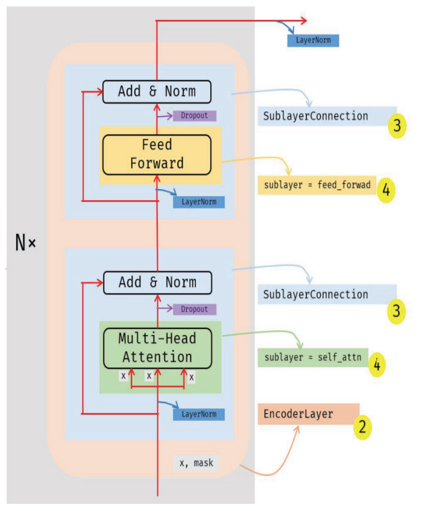
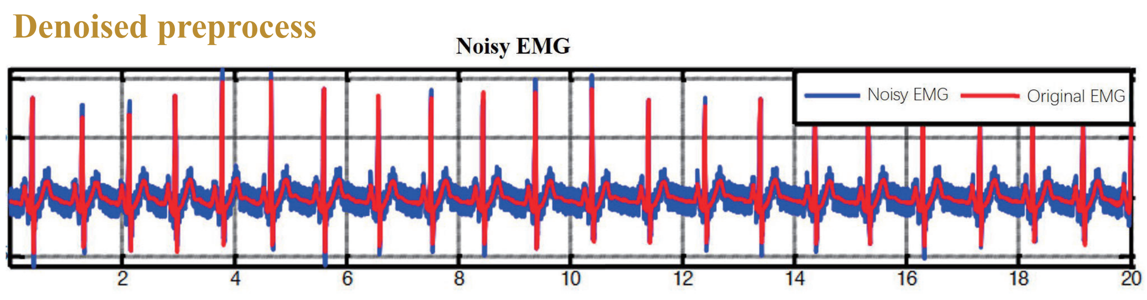
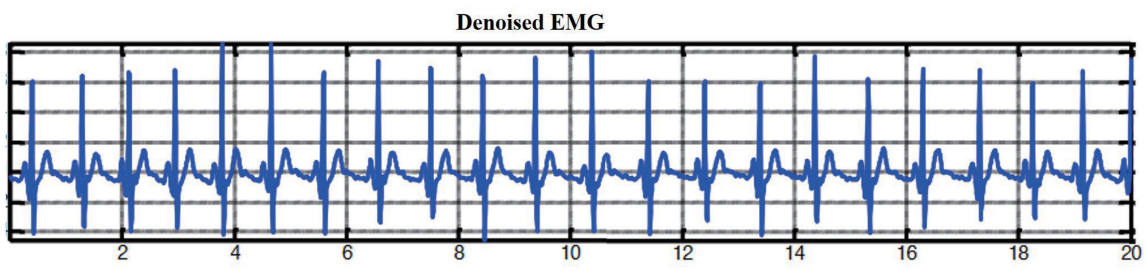


Fig. 8. Encoder realization

RESULT&ANALYSIS

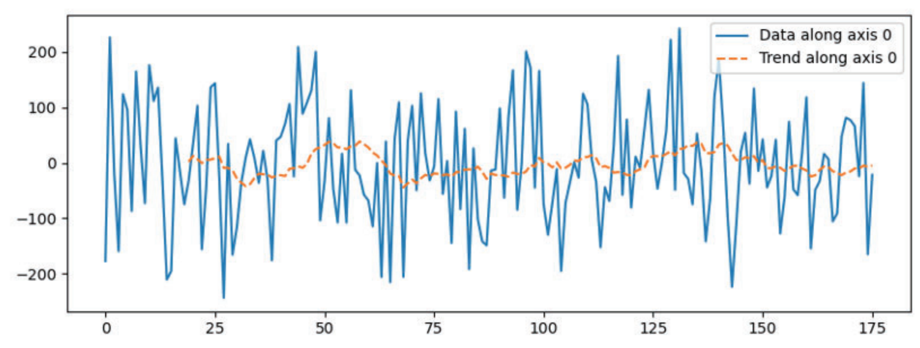
Denoised preprocess

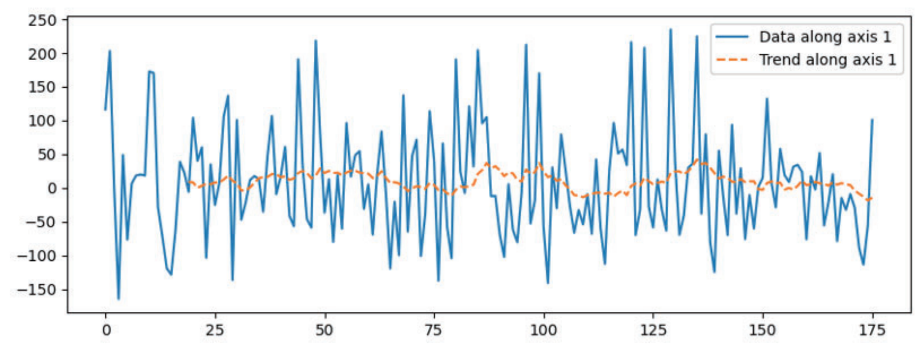


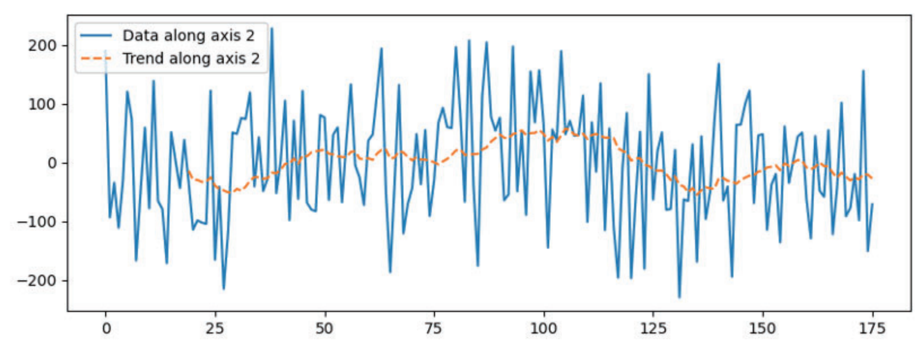


Result from network based on CNNs vs Transformer

	Patch size	Training R2 Score	Testing R2 Score
CNN	512*6	0.826433763	0.813832964
Transformer	100*6	0.489926425	0.454962983
	200*6	0.582114293	0.547119031
	512*6	0.631361944	0.594592771







KEY REFERENCES

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