

Abstract

This MSc Thesis proposes an approach for hand gesture recognition using temporal convolutional neural networks (TCN) and support vector machines (SVM). The goal is to develop a robust system for recognizing specific hand movements, applicable in prosthetics and human-computer interaction. The SVM classifier is applied to the Ninapro DB5 database, identifying five movements with higher accuracy. Pre-processing techniques, including filtering and normalization, are used to prepare the input signals for classification. To address limitations, a new database is created with volunteers affected by Multiple Sclerosis. The same pre-processing and SVM classification are applied to recognize the selected movements. The TCN model is employed to recognize hand movements in the Ninapro DB5 database. Varying input lengths and hyper-parameter optimization improve categorization accuracy. In conclusion, the proposed approach demonstrates hand gesture recognition using TCN and SVM. The new dataset and future research can further enhance system performance.

Introduction

The human hand is a powerful tool responsible for the sense of touch, enabling us to perceive the external environment. It is also a highly evolved means for physical and social interaction. The loss of sensation disrupts our existence, and the absence of tactile experiences appears to have more detrimental consequences than the absence of other sensory experiences.

Myoelectric signals (MES) have been extensively studied and utilized in various applications, particularly for recognizing the user's intention to potentially control assistive prosthetic limbs. MES is also used for estimating force and torque for activating the assistive device. sEMG signals measure electrical currents generated during muscle contraction, representing neuromuscular activities. Noise can affect sEMG signals as they pass through different tissues.

This thesis proposes methods for hand movement recognition using surface electromyography (sEMG) signals. Employed a Temporal Convolutional Neural Network (TCN) and a Support Vector Machine (SVM) classifier on the Ninapro database. Additionally, created a new database (DB) consisting of volunteers with upper limb mobility problems to assess the reliability. Optimized the SVM and TCN algorithms by selecting the best parameters and implementing appropriate data pre-processing techniques to enhance model performance.

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Methods and Materials

In order to recognize 52 hand movements from the 5th Ninapro Database, we proposed a TCN network and an SVM algorithm. Additionally, a new database was created, consisting of 20 patients with multiple sclerosis, following the same protocol and hand movements as the 5th Ninapro database.

Movements

abduction of all fingers
fingers flexed together in fist
wrist flexion
wrist extension
Pinch finger

Table 1. Hand Movements

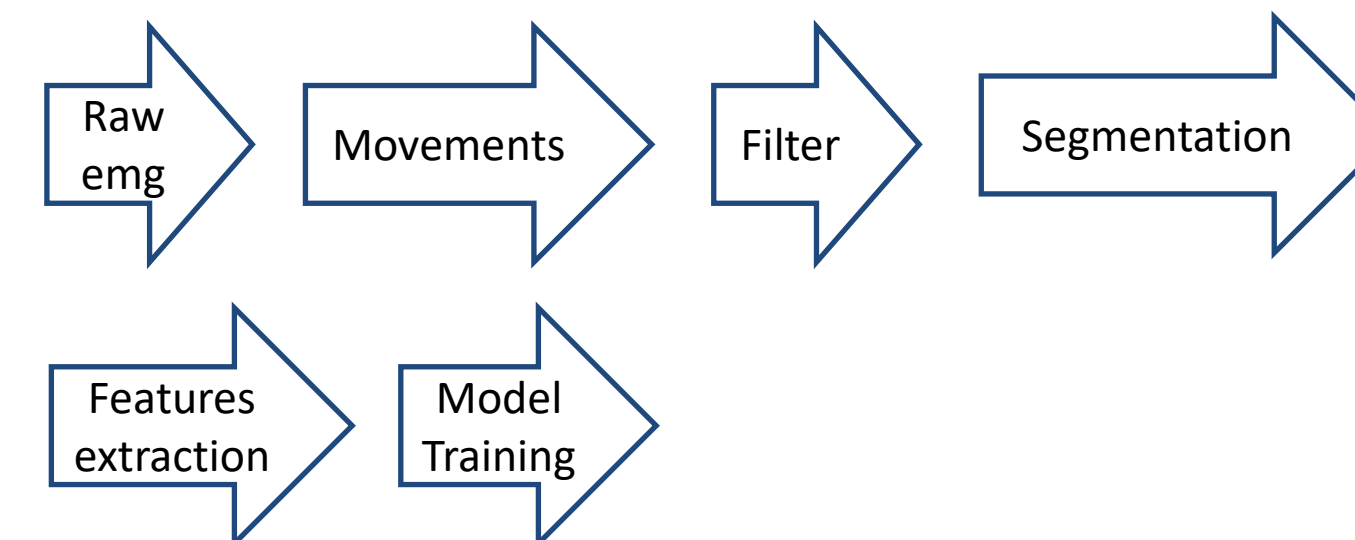


Figure 1. Emg Signal Processing

Firstly, the SVM algorithm was employed to recognize these 5 hand movements in both databases. Subsequently, the TCN model was utilized to recognize the same 5 hand movements based on the Ninapro database.



Figure 2. TCN Architecture

Results

Method/ Results	SVM Ninapro	SVM New database	Segmentation	Overlapping	Results
			750 ms	90%	76,64 %
	96,6%	97,06%	750 ms	99,3%	73,45%
			750 ms	60%	70,65%
			150 ms	60%	66,2%
			200 ms	75%	65,68%
			200 ms	95%	70,69%

Table 2. Results of SVM algorithm

Table 3. Results of TCN

Discussion

This study employed the fifth iteration of the Ninapro database as a fundamental dataset, alongside the creation of a novel database specifically tailored to individuals affected by multiple sclerosis, aiming to enhance accuracy in movement recognition. In order to establish comparability, a meticulous adherence to a standardized protocol was observed during the data collection process for both databases. Furthermore, a temporal convolutional neural network (TCN) was developed to optimize the precision and effectiveness of movement recognition.

Conclusions

In this study, we utilized the popular Ninapro database for hand movement recognition. Additionally, we created a new database solely consisting of volunteers with multiple sclerosis and upper limb motor impairments. The data collection followed the same recording protocol as the Ninapro database. To compare the two databases, we focused on gathering data with a common recording protocol. We selected 5 movements for recognition to minimize time and the number of volunteers required. The SVM deep learning algorithm confirmed the reliability of our database for researching and rehabilitating motor impairments caused by diseases. We also used a specialized electronic game and the Myo armband for user-friendly recognition of the selected movements. However, recognition using Myo was challenging for users with upper limb motor impairments. Therefore, a new specialized database is necessary. Finally, a temporal convolutional neural network improved recognition performance by 2.7%, especially in real-time scenarios.

Future Work

The recognition of hand movements is an area of significant interest, with many aspects that remain unexplored. Future research endeavours could focus on several objectives. Firstly, collecting data and creating a database from individuals with upper limb motor impairments, encompassing different levels of motor difficulties. This would provide valuable insights into various conditions, ranging from mild movement impairments to severe challenges. Secondly, developing machine learning algorithms trained on databases specifically composed of individuals with motor impairments. These algorithms could enhance the accuracy of movement recognition. Furthermore, comparing the performance of algorithms using the Ninapro database could offer insights into their efficacy in recognizing movements executed by individuals with motor impairments. Lastly, there is a potential to expand the range of successfully recognizable movements, thus broadening the scope of applicability in practical scenarios.

References

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