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Finger gesture recognition during hand movement with smart skin technology and deep learning

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Table of Contents

1 Introduction

Finger gesture recognition (FGR) is a rapidly developing field that utilizes a variety of technologies and has a wide range of applications, including human-computer interaction (HCI), sign language interpretation, virtual reality, patient rehabilitation and more. In recent decades different approaches were explored for solving the FGR task including Video analysis [1, 2], smart gloves [3, 4], smart bands [5], and surface electromyography (sEMG) [6, 7, 8, 9, 10, 11].

sEMG is an attractive enabling technique in this field as it captures the electrical activity of arm muscles located away from the fingers, so finger movements are not restricted. Additionally, it does not require a visual pathway, so it can be operated in a dark environment or while moving. It is also sensitive to applied force without any apparent movement (isometric muscle activation). Both low and high-density sEMG has been previously studied, however, contemporary sEMG-based FGR systems often require cumbersome electrode wiring and electronic instrumentation, making them difficult to use in natural settings[12,13].

Recent developments in smart skin technology have provided an opportunity to collect sEMG data in more natural conditions by transforming the recording device to be small, flexible, wireless, and steady on the skin. In a recent study conducted in Yael Hanein Lab at TAU, a soft 16-electrode array with a miniature and wireless data acquisition unit, and a deep learning (DL) network were used to classify finger gestures under natural conditions. This approach has been shown to achieve accuracy values as high as 92.5 ∓ 2 percent for 8 gestures, in a fixed hand position, when the training and test data are from the same recording session. High accuracy values have also been reported for training and test data from different recording sessions, with three different fixed hand positions [14].

While these results are promising, there is still a need to extend this work to free-hand movement. In this context, finger gestures are not limited to specific hand positions, but can be made in any orientation. This presents a challenge for sEMG-based gesture recognition, as the movement of the hand can affect the sEMG signals. Despite this challenge, the use of a soft electrode array with a wireless data acquisition unit allows a more natural use of the system, and the high accuracy values achieved to date suggest that sEMG-based FGR has the potential to be a useful tool in a variety of applications.

We aim to extend the work on sEMG-based finger gesture recognition from fixed hand positions to free hand movement, where finger gestures can be made in any orientation.

2 Objectives

a. Extend previous work on sEMG-based FGR to include free hand movements with the help of additional data from accelerometers and gyroscopes placed in the data acquisition unit.
b. Examine the possibility of creating a universal algorithm for cross-subject FGR.

3 Materials and Methods

3.1 Wireless sEMG system

This study employed a set of electrode arrays based on previously reported techniques. These arrays consist of carbon electrodes and silver traces screen-printed onto a thin, soft polyurethane film, which is then overlaid with a second double-sided adhesive polyurethane film for passivation and skin adhesion. The electrophysiological measurements were conducted using a wireless data acquisition unit (DAU) developed by X-trodes Inc. to allow for measurements in natural conditions. In addition to its 16-channel unipolar design, featuring a noise level of $2\ \mu V$ RMS, a frequency range of $0.5 - 700$ Hz, a sampling rate of 4000 samples per second, a 16-bit resolution, and an input range of $\pm 12.5\ mV$. The DAU is also equipped with accelerometers and gyroscopes. Those 3-axis inertial sensors allow for precise mhand acceleration and rotation measurement uring the sEMG recording. The DAU is powered by a $620\ mAh$ battery and has a maximum operating duration of 16 hours. It also includes a Bluetooth module for continuous data transfer and has both built-in SD card storage and cloud storage for offline data analysis. The DAU is controlled through an Android application [14].

3.2 Data collection

In this experiment, we developed an experimental protocol for data acquisition as follows: subjects will participate in 2 recording sessions on separate days. During each session, 4 different conditions will be performed, 3 of which involve a fixed hand position (referred to as hand position I, II, III in Figure 1), and the fourth condition includes moving the hand back and forth in hand position III (referred to as moving hand). Each condition will include 10 different finger gestures, and each finger gesture will be repeated 10 times consecutively for a duration of 5 seconds each. In total, for each subject, we will collect a total of 800 finger gestures which will be used to train our deep-learning algorithms.

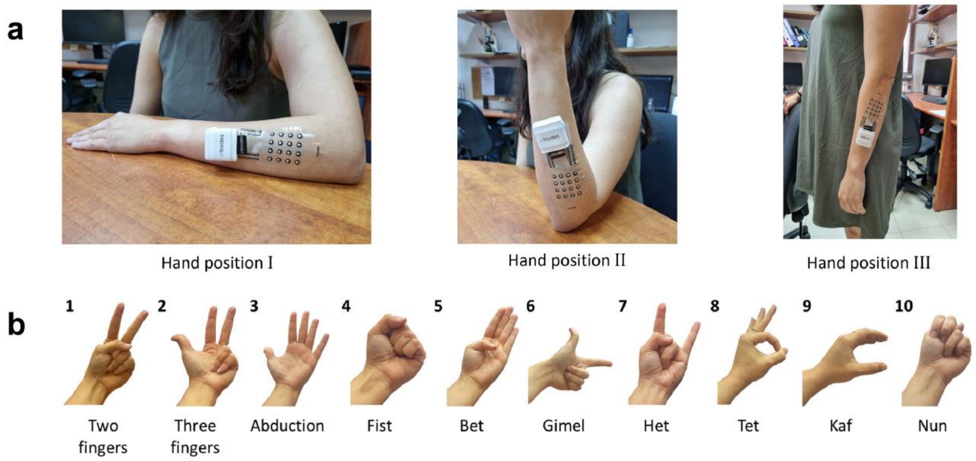

Figure 1. Data collection scheme. (a) The 3 hand positions examined in the experiment. (b) The 10 hand gestures examined in the experiment [14].

3.3 Data analysis

In this study, we begin by reproducing results from a previous study, hence we are utilizing proven algorithms as our starting point. However, since we are extending the capabilities of the algorithm to include freely moving hands, it is likely that the algorithm will be significantly altered. A variety of new algorithms will have to be explored to solve the new task, but the main concepts remain the same: filtering the sEMG data, segmenting the data, extracting features from each segment, training a deep learning or machine learning classification model, and classifying new data.

The algorithm will be compared on different classification tasks, as specified in Table 1. Tasks 1-3 is for reproducing previous results and enabling accurate comparison of the algorithm under different conditions. Our goal is to achieve a model that provides high accuracies in cross-session and cross-subject manners, and therefore we have chosen our tasks accordingly.

task	Training Data	Test data
1	X events from hand position II (all sessions).	Y events from hand position II (all sessions).
2	X events from hand positions I, II and III (all sessions, all subjects).	Y events from hand positions I, II and III (all sessions, all subjects).
3	All events from all hand positions from session 1, and only Y repetitions of each gesture from session 2, hand position II.	X events from session 2, hand position II.
4	X events from moving hand (all sessions).	Y events from moving hand (all sessions).
5	All events from moving hand (all sessions).	All events from hand positions I, II, III (all sessions).
6	All events from moving hand session 1.	All events from moving hand session 2.

Table 1 - the classification tasks, X represents 80% of the data while Y represents 20% of the data.

3.4 Deep learning algorithms

Machine learning algorithms, such as convolutional neural networks (CNNs), have been widely employed in the context of FGR. CNNs are a type of neural network that is particularly well-suited to image classification tasks. They consist of multiple layers of interconnected nodes, with each layer learning to extract increasingly complex features from the input data. In the context of sEMG-based FGR, CNNs are effective at learning to recognize specific gestures from sEMG signals at a fixed hand position [15].

Overall, CNNs have demonstrated to be a viable option for sEMG-based FGR when working with relatively small datasets. They can learn complex features directly from the data and achieve high levels of accuracy, making them a promising choice for this task [15,16].

3.5 Classification Pipeline

As described, the base algorithm in this study was taken from the previous research. raw sEMG data were subjected to filtering to reduce power-line interference using a combination of $50\ Hz$ and $100\ Hz$ comb filters. In addition, a $20 - 400\ Hz$ 4th-order Butterworth bandpass filter was applied to attenuate non-sEMG components. After this, the data were segmented manually (according to annotations) into time intervals for each gesture, referred to as active time windows [14].

These active time windows were then divided into 200ms sub-windows, and the root-mean-square value per channel was calculated for each sub-window, resulting in a grid of 16 values. This grid, referred to as an activation map, was input to a classification algorithm, such as a convolutional neural network [14].

In addition, a hidden Markov model was trained using sequences of activation maps from the training data. New maps sequences were generated and added to the training data to improve classification accuracy.

After conducting majority voting on the classifications of the individual sub-windows, the classification algorithm outputted a final classification for the active time window. The convolutional neural network used in this study consisted of two convolutional layers followed by three fully connected layers, as can be seen in Figure 2, and was trained using 1000 epochs with a learning rate of 0.0005-0.001 and a weight decay of 0.0001, using the Adam optimizer and dropout of up to 0.3.

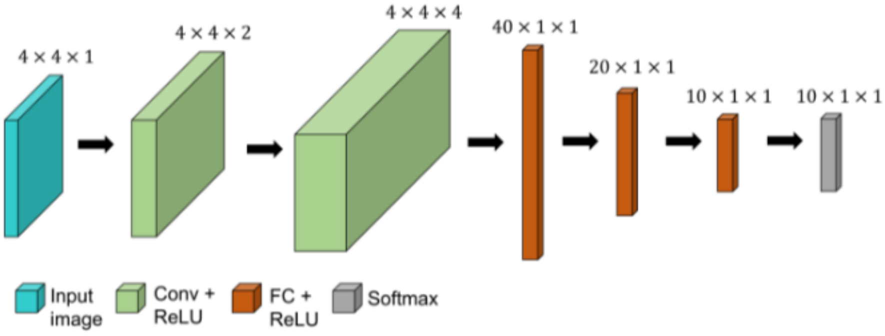

Figure 2: CNN architecture used to reproduce previous work [14].

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