TouchSense: Classifying and Measuring the Force of Finger Touches with an Electromyography Armband

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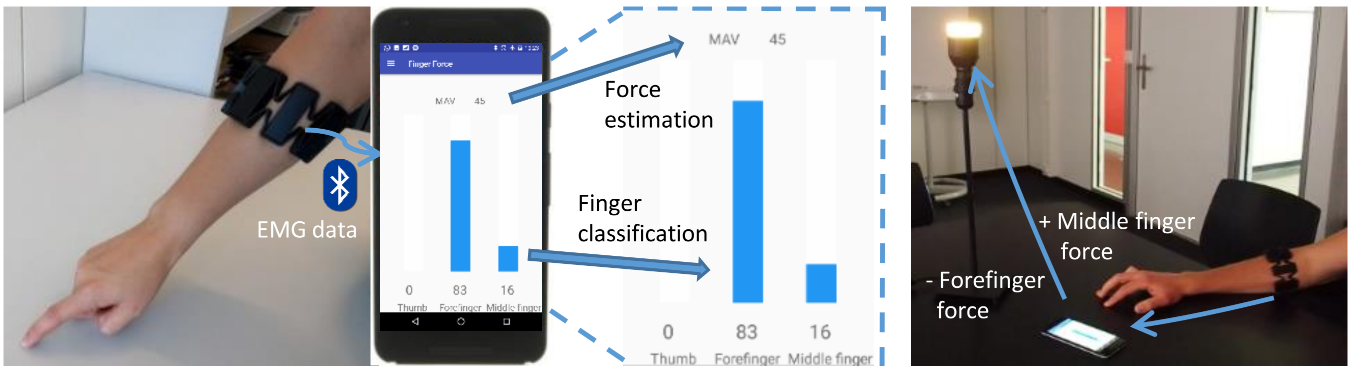

Figure 1: We propose a method which can turn any surface into a force-sensitive input modality by augmenting the user with an inexpensive and wireless EMG armband and a smartphone for running finger classification and touch force estimation. This enables new ways of interacting with appliances, such as a lamp for example.

ABSTRACT

We present TouchSense, a system to classify and to compute the force of finger touches using an inexpensive, off-the-shelf electromyography (EMG) armband. From EMG input only, we classify the finger touches and estimate the force applied when pressing an object or surface with the thumb, forefinger, or middle finger. We propose a novel neural network architecture for finger classification using EMG data. Our system runs in real time and only utilizes the Thalmic Labs Myo EMG armband and an Android smartphone, thereby being wearable and mobile. We showcase one application for our system, which controls the brightness of a lamp.

CCS CONCEPTS

• **Human-centered computing** → *Gestural input*; *Ubiquitous and mobile computing*; *Mobile devices*; *Haptic devices*;

KEYWORDS

Wearable Computing, Touch-based interfaces, EMG, Interaction, CNN

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1 INTRODUCTION

In our daily life, we frequently use our hands and fingers. We touch objects to sense their properties or actuate them. When interacting with natural objects or also people, the force we apply with our hands and fingers makes a difference in the interaction and also the obtained response. For example, when hitting a key on a piano very strongly, the piano emits a loud tone. Most technical appliances do not exhibit this behaviour and do not react specifically to which finger was used and how much force was applied. To continue the example above, no matter how softly or strongly you press a light switch, it will only turn the light on or off. Classifying the finger and measuring the force could enable new forms of interaction. To add this sensing capability there are two options, either augmenting the objects or the humans themselves. Augmenting all appliances is mostly very costly and difficult. Apple includes a force-sensitive display using its "Force Touch"[1] technology into newer products. However, this is only possible for limited display sizes. Augmenting the human on the other hand would make it possible to sense the finger force not only for specific devices, but for any surface in the human's environment.

[1] https://en.wikipedia.org/wiki/Force_Touch

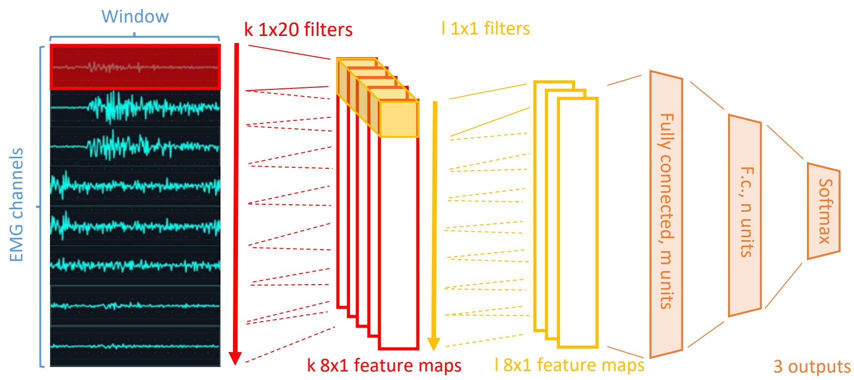

Figure 2: Our architecture for finger classification consisting of two convolutional layers with (k) and (l) filters, two fully-connected layers with (m) and (n) units, and finally a softmax layer.

A viable possibility to sense the force exerted by the fingers is to use electromyography (EMG) on the forearm, thereby directly measuring the activation of the muscle's controlling the hand and fingers. Prior research has shown that it is possible to use machine learning methods to reliably classifiy the finger used for touching and a coarse estimation of the finger's force [1–3]. However, there are several shortcomings: the EMG devices used are highly expensive with high sampling rates and high numbers of channels; the devices are heavy, electrodes are wired and the setup is tedious, therefore the systems are not mobile; finally, they only offer a coarse force estimate.

To address these limitations we create a system for finger classification and force estimation of the thumb, forefinger and middle finger, which is inexpensive, wearable and mobile, moreover runs in real-time and is session-independent, i.e. the system does not have to be trained before each use.

2 THE TOUCHSENSE SYSTEM

Data collection. To collect EMG data, we use an inexpensive Thalmic Labs Myo[2] armband, which is worn on the forearm. It consists of eight EMG sensors, which sample at a rate of 200 Hz. The data is transferred to a smartphone via Bluetooth. All further processing takes place on the smartphone itself. We asked participants to perform multiple finger presses with the thumb, forefinger and middle finger at different strength levels and also changing the strength while pressing. To collect force ground truth we used a hardware setup containing three force-sensitive resistors to obtain absolute force ground truth values. We recorded data from eleven participants (three females, 20 to 66 years old, age average of 28.9 years). For seven participants, we collected a second EMG session for a session-independent evaluation.

Preprocessing. We segment the EMG data into 100 ms windows which we use for training a neural network for finger classification. Employing a neural network frees us from the need of engineering features, as done in previous work. As the inference should run in real time, the challenge is to design a network which performs well, but has a low inference runtime.

Finger classification. We propose a novel convolutional network architecture for EMG data consisting of five layers as shown in Figure 2. The first convolutional layer learns features for each EMG channel, the second combines these per-channel features into fewer higher-level features, which are the input to two fully-connected layers, followed by a softmax layer for calculating the classification decision on which finger is used. We implement and train the network in Tensorflow and run it on an Android smartphone. The model size is under 50 KB and the inference time is under 3 ms, enabling real time applications. We evaluated our classification system in various experiments. Using all the participants' data for cross-validation, we reach an accuracy of 91.2%, showing that our network is able to correctly extract information from the EMG signal. When training a session-independent classifier per participant, we reach an accuracy of 67.6% for all three fingers and 82.3% when using only the thumb and middle finger.

Force estimation. To estimate the finger's force, we use a simpler approach. Over the same window that is used for classification, we calculate the mean of the absolute values over all EMG channels. This estimate has a high correlation to the real force values measured in the data collection trial. Further, with regression models we can estimate the force value.

Application. We implement a demo application in which we control the brightness of a smart lamp with the forefinger and middle finger as shown in Figure 1. Pressing with the forefinger reduces the brightness, pressing with the middle finger increases it. The lamp itself is not required to have any controls as we can us the surface around it as an input surface. Moreover the change in brightness adapts to the force applied with the fingers, the stronger the press, the larger the change.

3 CONCLUSION

We presented TouchSense, a wearable system to sense the finger used in touch gestures and the force applied by that finger. We proposed a novel light-weight neural network architecture for classification on EMG data, which runs in real time. Using only a smartphone and a Myo armband, our system is completely mobile. In the future, we plan to extend the neural network to also directly regress the force through the network instead of applying a second processing step and also to allow combinations of fingers.

[2]www.myo.com

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