Multichannel EMG Biometric Signal Processing

Introduction

Controlling technology with the flick of the wrist is a concept widespread in works of science fiction, from interacting with holographics on a futuristic space station to simply replacing a touch screen with gesture controls. The idea that we can manipulate the screens in front of us, or even the world around us, without touching anything (especially post covid), sparks the imagination and can feel like magic. The realization of this idea however, is much closer than most people might think. With new hardware solutions from non-invasive myo armbands [1,d] to extremely invasive systems such as Neuralink [3], mind control of a computer is in the foreseeable future.

If this is true however, why are we not already using this technology? For wearable devices such as the electromyography (EMG) controlled myo armband, the short answer is that the software is not robust enough to handle real-world biometric data [1,4]. There are a lot of components that go into processing biometric data and different wearable devices use a varying number of channels and types of sensors to collect this data.

This proposal focuses on three key components (TKC) that multi-channel EMG wearable devices have struggled with [6,7]:

- Classifying new gestures
- Generalizability across users
- Efficiency in processing time

These components are necessary for the success of any commodity wearable. When a company or the general public talks about the accuracy of a device in determining step count, heart rate, gesture control, or activity level, whether they know it or not, they are referring to the device's classification capabilities [8,9]. The TKC listed above are directly responsible for a device's classification capabilities.

Preliminary research to this proposal has found that there are two major technical challenges to advancing these TKC that current EMG research has not addressed. These challenges are:

- Sensor shift
- Classification Optimization

This research is novel in that the proposed solution to the challenge of sensor shift is adaptive wearablorientation data preprocessing for wearable devices. Classification techniques can be accelerated using parallelization for multi-core processing without changing the fundamental methods of the classifier.

Importance and Background

The classification capabilities given by the above TKC are very important for two reasons. First, the classification capability will determine the usability and functionality of the device, especially in the case of a wearable used for gesture control of another computer product, (eg., a

[1] Open source database 1: https://archive.ics.uci.edu/ml/datasets/EMG+data+for+gestures#
[2] Open source database 2: https://github.com/UlysseCoteAllard/MyoArmbandDataset

prosthetic, a virtual reality (VR) game, a smartphone, etc.) [6, 9-11, a-c]. Second, the accuracy of a wearable device used for fitness or other self-quantifying attributes can affect both the mental and physical health of the user [8-11].

For example, in a state-of-the-art EMG controlled prosthetic device, only a set number of gestures can be performed [12, h-l]. Prosthetic users cannot move individual fingers, often cannot create new gestures for their device to learn, and may suffer from high gesture misclassification rate [13, k,l]. High gesture misclassification in a prosthetic would be similar to a keyboard with broken keys that don't always respond or sometimes get stuck. This can make daily tasks frustrating to the point that some prosthetics users opt for a mechanical prosthetic device that won't drop items due to poor bio-signal processing [k,l].

When applied to wearable devices used for fitness and self-quantifying attributes, inaccurate classification can lead users to believe that they are meeting their goals when really they are under or over-performing [8-11]. In the case of over-performing, this can have a negative impact on users who must maintain a level of activity but must not over-exert themselves, such as someone who is in rehabilitation or pregnant [10,11]. In the case of under-performing, this can negatively impact those who need to meet a certain level of activity for weight loss or heart-health [8].

Examples outside the medical and prosthesis field, include Thalmic Labs', and now CTRL-Labs', wrist-based gesture control myo-armband. This armband uses 8 EMG sensors in an array around the user's forearm to detect muscle activity as shown in **Fig a**.

Figure a. Left: Thalmic Labs' Myo armband [d]. Right: Facebook's Reality Lab's (FRL)/CTRL-Labs' wrist-based emg wearable [e]

Since the armband's release date in 2013, and to this day despite being discontinued, research has been conducted about or using this product [14,15, add more]. However, no research has been found to identify new gestures in real-time, real-world settings using only the wrist-based sensor data. Researchers such as Andronache et. al. have made great strides in modeling techniques that can classify 13 gestures with a 99.31% accuracy but these high accuracy, high

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gesture recognition results are only established because the experiments are done in a controlled lab setting. In Andronache et. al's paper the researchers clearly state that the myo armband used was kept in the same position at all times through all gestures [16]. In real-world settings, high accuracy results like this can be over 100 times worse when the wearable device is not kept in a constant controlled position [4].

Other researchers such as those found in [a-c, f], have also found their research to yield high accuracy results in lab settings but these results have the same limitations for the TKC in real-world applications. As stated above these TKC (three key components) are: new gesture classification, generalizability across users, and processing efficiency. Research in [g] is able to address new gesture classification but relies on camera sensor fusion; meaning that they use visual processing to identify and label gestures which requires additional processing time and separate non-portable systems for visual capture. Research in [10,12,16, m] can yield high gesture count, high accuracy results but rely on controlled lab settings that do not account for normal activity or user set-up. Research in [a-c] also yields high gesture and/or high accuracy results but requires resource intensive machine learning that cannot be done on a portable device.

Classification techniques, especially those that use a form of machine learning, have been studied extensively and the optimization of these techniques have been studied just as much [p-t]. Research conducted in [p,q] shows that EMG data recognition can be optimized using parallelization. However the degree of optimization and reproducibility of results depends on the recreation and execution of the parallelized program. Since studies like these are not about their code structure but rather the viability of their methods, it becomes clear that EMG classification can be optimized using multi-core parallelization but that further research is necessary to create more reproducible programs.

The above research, and preliminary analysis of open-source EMG data[1,2], has led this research to identify that the two major technical challenges for the TKC are sensor shift and classification optimization [n,o].

Research Plan

Sensor Shift

Starting with open-source EMG data from [o] and the related research in [f,f1], this research will begin by classifying the provided gestures using the same means as the related research (deep learning using transfer learning) as a classification proof of concept. The gestures to be classified are shown in **Fig. b** from [f,f1].

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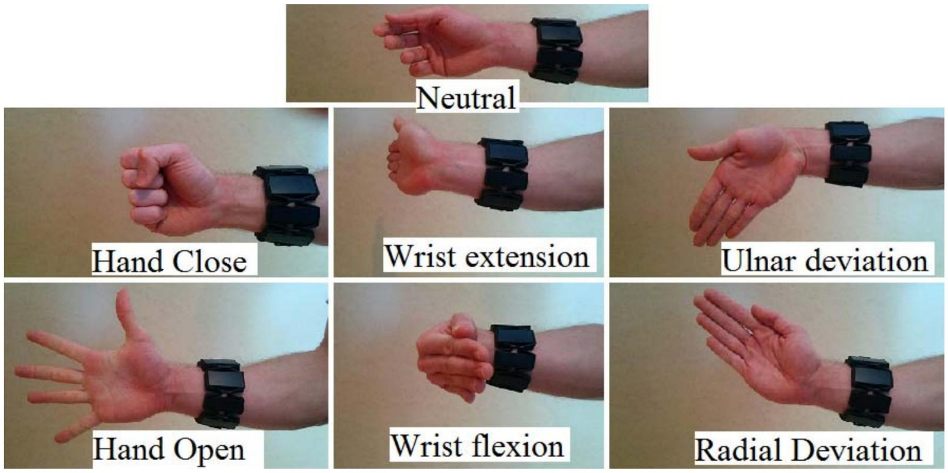

Figure b: Myo armband hand gesture positions [f, f1]

If for whatever reason, this proof of concept does not come to fruition, then the research will take a more well unknown classification approach such as linear discriminant analysis (LDA), support vector machines (SVM), Bayesian statistics, or artificial neural networks (ANN).

Once a classification proof of concept has been established, there will be an assessment of sensor shift in the data. Possible sensor shifts are shown in **Fig c.** below but sensor shift is not limited to those shown.

Figure c: Myo armband at different positions on the forearm and wrist [f,f1]

Artificial sensor shifts will also be applied to individual data sets to simulate shifting during use, not just from initial placement. The goal of this process is to create an adaptive algorithm that can identify:

a. When the shift takes place
b. The new position or orientation of the shift
c. If the sensor data can be adjusted or relabelled internally for the classifier

The hypothesis that this research makes is that, if the device can identify when and where the sensors shift, then by adapting the sensor data the classifier will remain functional and optimal.

Classification Optimization

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The second stage of this research is not dependent on the first stage but will benefit from the success of the first stage. This second stage will parallelize multiple classification techniques to take advantage of multi-core processors. The classification proof of concept will be the first optimized algorithm. From there more resource expensive but high accuracy classification methods will be moved from sequential execution to a parallel structure. The goal of this stage is to create and publish a reproducible program for parallized classification methods of EMG gestures.

The hypothesis for this stage of the research is that, if classification techniques are parallelized for multi-core processors, then they will be more efficient and able to run on portable devices.

Skills & Resources

This research will benefit from the many resources available at Northern Arizona University (NAU). These resources include Monsoon, a high performance computing cluster that may be needed for accuracy comparisons of resource intensive machine learning classification algorithms on large datasets. The Wearable Informatics Lab (WIL) at NAU, which specializes in wearable technology, will be available for advice and equipment. The advisor of WIL, Dr. Kyle Winfree, will be taking a research advising role for this project. The School of Informatics Computing and Cyber Systems (SICCS) department at NAU has a wide range of computer science professors who are experts in their fields of machine learning, parallel programming, and data sciences.

Broader Application

Restate importance and give details of applications

Narrowing the scope of this research to EMG wearables, more specifically to the technical issues of sensor shift and classification optimization for wearable devices, allows this research to have a much broader application. The wide field of wearable devices has no shortage of research investment, however much of this research is focused on increasing accuracy or gesture recognition count by creating new and possibly more complex machine learning programs. This research is different as it will allow those novel techniques to be usable in real-world applications by addressing their technical challenges of sensor shift and classification optimization.

By working on the root issues of EMG signal processing, sensor shift and classification optimization, this research addresses a foundational step in wearable devices' classification capabilities. The application of this research is boundless in that the technology that can benefit is only limited by our ingenuity. The technology that has advanced from biometric signal processing in the past include but are not limited to:

- Fitness devices [8,9,11]
- Medical devices [7,10]
- Mobile devices [1]
- Gaming devices [ref 4]

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Drones, phones, and working from home [ref 5] can all benefit from real-time, real-world, advancements in biometric signal processing as this field is the next step in human-computer-interaction. Going from touch-screen to touchless-control is no longer science fiction which is why big tech companies like Facebook and Amazon are currently researching EMG wrist-worn controllers [1,2,e]. Between VR gaming and VR offices, robust classification and control of a virtual environment is becoming a necessity if such applications are going to be successful to a broad audience.

Within the medical field, this advancement in EMG signal processing is especially important when EMG sensors are used in prosthesis, rehabilitation, and even seizure detection [10,12,f,u].

Conclusions

A form of biometric processing is used in all wearable devices. Wearable devices rely on accurate classification methods to function for the general users. EMG wearable devices are not a new technology within the medical field, but advancements in the technology have allowed them to become relevant to a broader audience. While EMG wearable hardwear have advanced significantly in recent years, the software leaves much to be desired by consumers.

This research addresses three key components (TKC) in multichannel EMG signal processing that current research has struggled with; which include classifying new gestures, generalizability across users, and efficiency in processing time. The technical challenges identified for these TKC are sensor shift and classification optimization. This research proposes solutions to these challenges in two non-dependent stages. The first stage will create an adaptive algorithm to identify, locate, accommodate sensor shift. The second stage will optimize classifiers to completely utilize parallel architectures accelerating their performance for real-time, real-world use.

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