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Q&A

How did you become involved in doing research?
I started by meeting with EECS faculty whose research I knew about. What does your lab do? What position or project do you think would be well-suited to an undergraduate? These were the kinds of questions I would ask. They were very helpful; professors enjoy talking about their work. But there was one question they often asked me that stuck with me: what is it you want to do? From this question I realized the most important part of research—do what you love. Anything can be research, provided somebody has an interest to investigate it. Because I had always been fascinated by building computer systems that interact naturally with people, I thought it would be fun to build a project around this idea.

How is the research process different from what you expected?
Honestly, I didn't really know what to expect. I thought working as a "research assistant" might be a lot like any other job. In a way that's true, but I now believe research is more like school. There are papers to write, tests to perform, formulae to solve... all the sorts of problems I might encounter in the classroom. However, there is one important difference, and that is that I was the one deciding the next steps. I didn't have a teacher telling me what to do and when to do it. Rather, I had a personal goal of what I wanted to show and had to meet with my mentors to work out the plan to get there.

What is your favorite part of doing research?
I love learning, and to me, research is like the opportunity to get paid to learn. Of course, there is a lot of work involved, but I feel that it is very rewarding. When a research project is complete, you've acquired a lot more skill in the field and, hopefully, accomplished what you set out to do.

An analysis of electromyography as an input method for resilient and affordable systems: human-computer interfacing using the body's electrical activity

Seth Polsley

ABSTRACT
As hardware continues to become smaller and faster, software becomes more powerful. The continual improvements in our technology promise to bring about significant changes in our lives and in how we interact with the world around us; new and popular devices with touchscreens and voice interfaces are evidence of this. Yet, even the most cutting-edge consumer devices have their limitations. For example, many individuals are still unable to use modern computers because of accessibility restrictions. Rehabilitation devices, such as robotic orthotics, and military projects, like exoskeletons, have not been fully realized using existing tools. Even in the massive computer-gaming industry, a device's interface can be as much a distraction to the player as an aid. An emerging field of interface technology may be able to help

solve some of these problems: natural interfaces that seamlessly interpret our bodies' biological signals. Electromyography (EMG), the recording and processing of muscular electrical activity, is one of these technologies. EMG shows a lot of promise, especially in rehabilitation and accessibility, but it has yet to become a mainstream technology. This work studies EMG through the construction of an EMG-based interface, considering its cost and reliance. The analysis seeks to determine the plausibility of implementing EMG systems in consumer devices, as well as examining some of its potential when applied to new problems.

Keywords—electromyography (EMG), neural network, Fourier transform, signal classification, human-computer interfaces

INTRODUCTION

In the past few decades, technology has significantly altered our lives. The digital revolution saw changes not only in electronics themselves, but also in the way we interact with them. Once mostly relegated to office workers and hobbyists, computers have become vital components of nearly every tool we use, and the integration of computers into so many electronics has paved the way for new human-computer interfaces as we seek to find better and more appropriate ways to control them. For example, the keyboard and mouse were long the standard in computer input technologies, but these devices were not very practical as a means of controlling telephones. For that reason, many modern cell phones now use touchscreens to interpret user commands. Touchscreens allow for very reliable and mobile device control, but they necessitate the use of hands. To allow hands-free control, voice interfaces have become increasingly popular in recent years. These interfaces have continued to advance, and as they improve, they have been able to understand humans more naturally.

However, even with our most advanced consumer-level technologies, like digital voice assistants and touchscreens, there are still those who cannot use these devices. Particularly, those suffering from physical disabilities or certain types of mental disorders may be restricted in their ability to interact with computers. The search for universally accessible technology is an open project in the scientific community. The continuing developments in hardware that allow for smaller and more powerful devices have led to growing interest in a new class of computer interfaces [1]. These types of interfaces would interact with users solely through their bodies' natural signals. The gold standard of this field of devices would be a true brain-computer interface (BCI). A BCI could, theoretically, interpret any user's action by monitoring his or her brain activity. Such an interface removes accessibility restrictions and has been used successfully in a large number of studies as evidenced in [2][3][4][5] and many more. A BCI would supersede all existing technologies since it would interpret commands directly from the source, our brains. BCI is a growing field that shows a great deal of promise; within the last decade alone, hundreds of new laboratories have been created to research BCI [6]. Unfortunately, most methods of monitoring brain activity, such as electroencephalography (EEG) or Functional Magnetic Resonance Imaging (fMRI), require expensive, specialized equipment in carefully controlled environments. These limitations are currently preventing BCI from spreading much beyond the world of research.

There are many other options than BCI that could make technology more accessible. Heart rate monitors in watches are an example of consumer devices that interact with the user based on his or her body's signals [7]. These rely on sensors that are inexpensive and reliable, in many kinds of environments [8]. The existence of such devices demonstrates that the hardware and software for more natural interfaces are available. One technology that may be viewed as an intermediary to BCI is electromyography (EMG), the subject of this analysis. EMG is the measurement of electrical activity across muscle groups. To understand why EMG is beneficial, recall that BCI often uses EEG. EEG measures the electrical activity of the brain. The popular, non-invasive techniques do this through an array of electrodes placed on the scalp. Unfortunately, these signals are difficult to acquire outside of controlled conditions, due to signal attenuation caused by the skull. Conversely, muscular electrical activity is much more pronounced, making it easier to detect. In fact, in many BCI applications, EMG is considered interference because it is so strong compared to EEG [9]. The relative strength of EMG enables EMG-based systems to use less expensive hardware. The stronger signal acquired by EMG is also more noise-tolerant than EEG.

Not only can EMG be more affordable and reliable than EEG, it also offers some of the advantages of BCI. One prominent example is in the field of physical therapy and rehabilitation. EEG has been successfully applied to a number of rehabilitation applications. EMG is also applicable to this field [10][11][12]. Furthermore, EMG could be paired with types of robotic orthotics to aid in rehabilitation for individuals suffering from more severe conditions, such as spinal cord injury [13]. The applications are not just limited to therapy. Specialized hardware like braces and exoskeletons could be driven by EMG, giving the operator a much more intuitive control than an interface using levers and buttons. Virtual reality systems, video games, and even general computer interfaces could employ EMG to give users an immersive and natural experience. It would be challenging to apply most modern interface technologies to many of these applications, yet BCI and EMG-based systems would be well-suited to them.

EMG is a very promising field for its combination of low-cost and reliability with a number of the advantages of more difficult interface methods such as EEG. This promise bears investigating and is the impetus behind this analysis. This paper outlines the construction of a very basic, end-to-end EMG system. In developing and building the final system, factors such as cost and noise-tolerance are considered. The resulting construct is also tested on a specific problem—distinguishing between two distinct movements of the arms. These tests are primarily intended to be demonstrative, not fully investigative of the developed system's capabilities; as discussed, there are of course many other possible applications.

METHODOLOGY

In order to analyze the effectiveness of EMG with regard to its cost and reliability, a complete EMG system was constructed. The developed system was composed of three primary components: the hardware, middleware, and software. Figure 1 shows an overview of the system. Briefly, the hardware is a small circuit that acquires the raw EMG signal. Middleware is being used in this case as a general term for all of the operations performed between the hardware and software; in this problem, the most important action is the analog-to-digital conversion (ADC) at a given sampling rate. The software is the portion of the system that does meaningful operations on the EMG data. In the tests performed, the software determines when muscle movement occurs and classifies the activity. A more detailed discussion of each section follows.

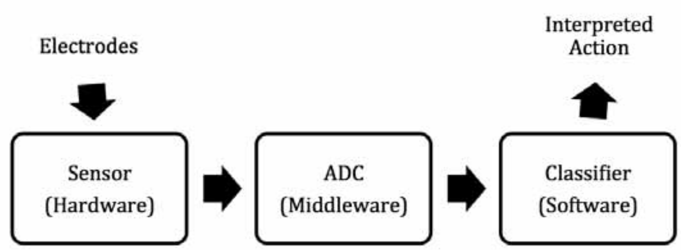

Fig. 1 Block-level view of the EMG movement classifier.

Hardware

The goal in the hardware phase of the project was to build an inexpensive yet functional EMG sensor. While there are some EMG schematics available online, such as the Advancer Technologies sensor seen in [14], many of these heavily pre-process the signal. The few sensors that are available for some consumer applications often only measure a single value, which is the amplitude of voltage across a muscle. Recording only the level of muscle activation removes a lot of potentially useful information from the signal; it certainly reduces the number of techniques that could be used with EMG that are found in current EEG systems, like spectral analysis. With the motivation of maintaining as much information from the original signal as possible, the final circuit was relatively simple. The circuit schematic is shown in Fig. 2.

The essential piece of the circuit is an instrumentation amplifier. Instrumentation amplifiers are ideal for this type of application because they measure the voltage

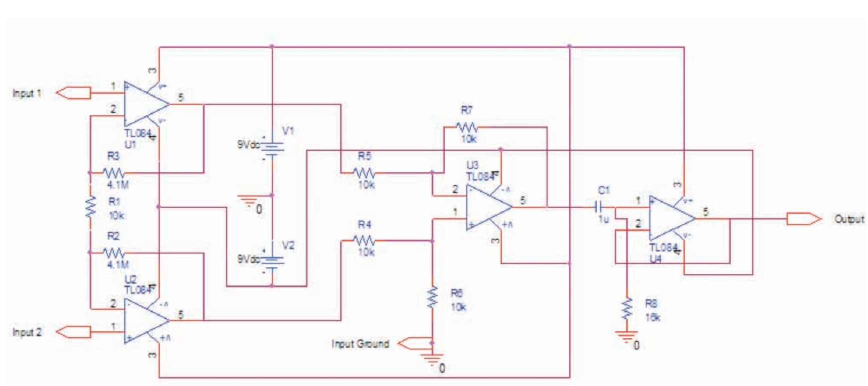

Fig. 2 Schematic of the instrumentation amplifier used as an EMG sensor.

between two points without heavily contaminating the signal. The amplifier's design is based on the discussion provided in [15]. TL084s were used as the op-amps because their JFET-based implementation helps to reduce current leakage on the input. Certain component values were selected based on recommendations provided in [16]. The resistors R2 and R3 were responsible for determining the gain, and their values were selected for a gain of 820, boosting the signal strength significantly. A large gain was preferred so that small muscle movements could be easily detected. Following the acquisition and amplification, some minor filtering is performed using a passive high pass filter with a cutoff frequency near 10 Hertz (Hz). This filter reduces the low-frequency components of the signal and is primarily intended to remove noise introduced by the sensor's batteries. More extensive filtering could be applied to examine specific bands, but in keeping with the goal of maintaining as much of the original signal as possible, no more filtering was done at this point.

There are three electrodes used as the input to the circuit: a global ground and two placed side-by-side across the muscle group of interest. The two electrodes on the muscle are used to find the voltage across the region of interest. This voltage is then referenced to the global ground. The signal goes through the amplification and filtering, and the final analog signal is sent on to the middleware.

Middleware

The middleware is the portion between the hardware and software. It abstracts all of the hardware away by providing digital measurements at a requested rate. A Bluetooth-enabled Arduino microcontroller, the BLUNO, was used for this part of the system. The BLUNO's ADC can sample analog signals between 0 and 5 Volts (V), converting them into a digital value with 10 bits of resolution; these parameters were quite sufficient for this problem. The BLUNO sends the digital value over a serial connection, either USB or Bluetooth. The USB interface was used in this project, even though the Bluetooth interface could be used for wireless applications. As an Arduino-based device, the BLUNO was programmed in the C language with a process that listened for new connections and would stream the EMG signal at the defined sampling rate.

Software

The software used the EMG data to assemble a feature vector and classify the user actions through a neural network.

1. Building the Feature Vector

A feature vector is a matrix of values, ideally those that are the most distinct across a number of different classes, used by a classification algorithm to learn and classify data. Since the task was to distinguish between movements, a feature vector had to be built to represent movements in a classifiable manner. Using thresholding, whenever a measurement above the threshold of 0.5 V is detected on the amplified signal, the next 120 milliseconds (ms) are assumed to be the beginning of an action. This time window was selected based on prior research suggesting there is up to an 80ms delay between when the electrical activity of a movement becomes recordable and when the movement actually begins to occur [17]. Of course, a 120ms window adds at least 40ms of delay over the body's natural one, with some extra latency due to sampling rate and processing time, but a 40ms delay is sufficient in most user applications. Indeed, delays of approximately this length are found in many consumer-level interfaces such as keyboards and touchscreens [18].

The collected samples in the 120ms window are then transformed using the Discrete Fourier Transform (DFT). The DFT, a form of spectral analysis, alters the signal so that levels of activation of certain frequencies may be examined. The DFT is also the reason a 120ms window was selected instead of an 80ms one, since the number of samples in the time window determines the resolution of the transformed signal, and the 120ms window contains more samples. To further increase the resolution of the DFT, the window is padded to twice its original size using zeros. The resulting resolution is the Nyquist frequency divided by twice the original number of samples (Nyquist_frequency/[2*time_window*sample_rate]). The Nyquist frequency is always half the original sampling rate because half the values returned by the DFT are complex. With a sample rate of 256 Hz, the resolution was approximately 2 Hz. Figure 3 demonstrates construction of a feature vector.

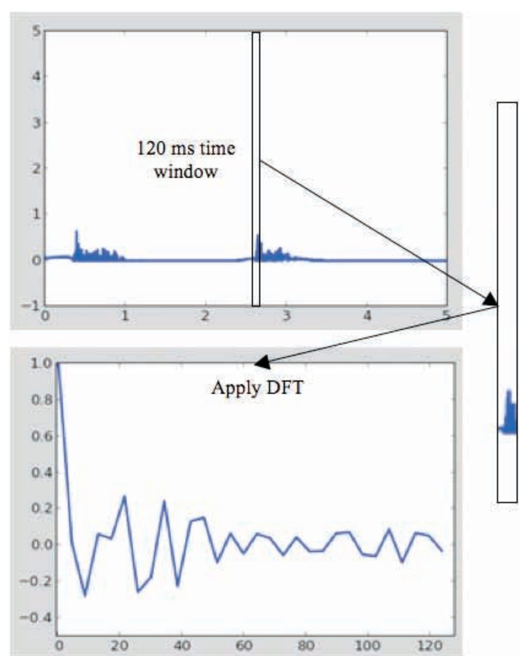

Fig. 3 A visual representation of building the feature vector

2. Classifying Movements

Classification is performed by a neural network with variable layer sizes. Neural networks are mathematical constructs that use layers of artificial "neurons" to learn how to classify some given data. For these tests, the input layer consisted of thirty neurons, the number of samples in the DFT, eight hidden neurons, and two output neurons. Only two outputs were necessary because the classifier was being used to discriminate between two movements; more movements could be added, but would require more output neurons.

Neural networks use supervised machine learning algorithms to classify signals, so before any meaningful results could be obtained, the network had to be trained. Training is implemented as an automated process wherein the user is instructed which action to perform and when. Training may be done in real-time or in batches because the software includes an additional feature of saving all the collected EMG data, along with the trained neural network's weights, at the end of each session. This information could be used for later batch training to improve classification accuracy. The trained network is loaded at the start of each new session, allowing the same network to be used repeatedly, whether training or classifying.

The final part of the software that merits discussion is the interface. Three plots are used to provide users with feedback and report the classification results. The first plot is a live graph of the acquired EMG data, which serves as a visual of muscle activity over time. The second plot is the DFT used for movement classification. The DFT demonstrates how much each frequency contributes to the muscle movement, dependent on the resolution of the transform. The final graph is used for classification reporting. The output from a neural network is the probability that a given input belongs to a specific class, and by taking the maximum output, the most likely class can be found. Thus, a plot of the output is not needed, since only the class must be reported. However, the plot provides the user with more information by indicating how certain the network is of a given input. Information like this can be helpful in determining how much more training is needed, especially when the training is performed live.

The resulting system is pictured in entirety in Fig. 4. As shown, the hardware phase was implemented on a breadboard, with clips for the leads to electrodes. The BLUNO's ADC is directly connected to the output of the sensor, and a USB connection links the software to the other components.

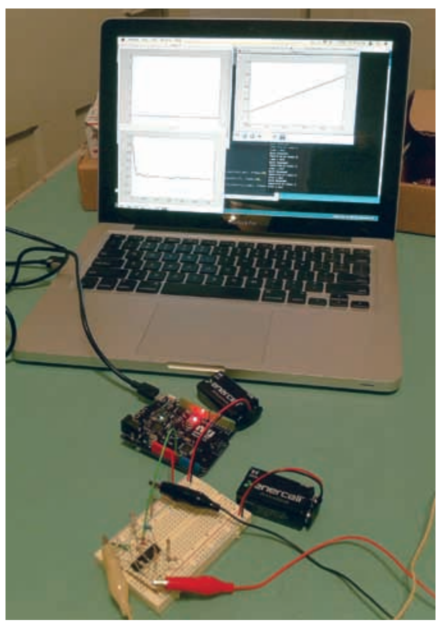

Fig. 4 The completed and assembled EMG system

RESULTS

By this point, the discussion has included the construction of an inexpensive EMG sensor built from a few circuit components and a microprocessor. The next phase of the analysis was to explore the capabilities of the sensor through testing. The test selected for this examination was the discrimination between two distinct movements of the bicep.

First, the electrodes were placed on the arm as shown in Fig. 5, with the ground electrode placed on the elbow. Areas over bones are ideal grounding points since there is little interference from the muscles in these regions [16]. Once attached to the EMG system, with the software launched, the training could begin. In these tests, all training was done over a set of live sessions, where the experimenter was connected directly to the system performing the indicated actions. As anticipated, the network was not able to classify correctly during the early part of the training, but after several hundred examples, classification accuracy increased noticeably. Following training, the resulting network could be tested on only its classification

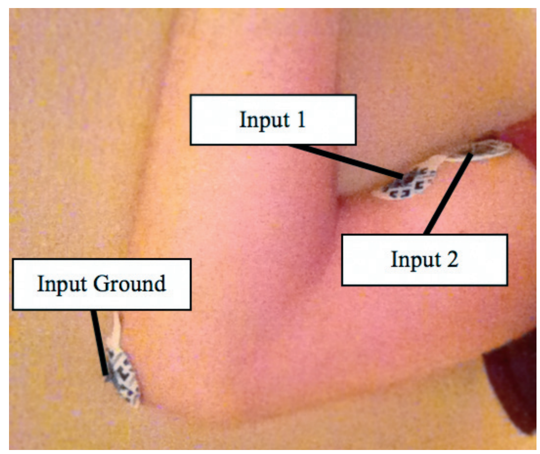

Fig. 5 Electrode placement for the experiments

accuracy. Six trials were run in all; Table 1 reports the individual trial accuracies. An average of all six trials indicated an accuracy of 74 ± 6 %.

Classification accuracy across multiple trials	
Trial Number	Accuracy
1	64.3%
2	77.1%
3	68.5%
4	71.4%
5	75.7%
6	84.3%
Average Accuracy	
74 ± 6 %	

Table 1

Figures 6a and 6b show the average-case DFT for both classified actions. The first action in Fig. 6a, which was sustained holding of an outstretched arm, demonstrates a roughly exponential drop in frequency activation, which is a typical phenomenon observed in EMG and EEG [19]. The second action seen in Fig. 6b, which was making a clenched fist, has a very different DFT. Notably, there is more activity in some of the higher frequencies, while frequencies around the 10 - 20 Hz range are more suppressed. These differences were sufficient for the neural network to distinguish between the two activities in most cases, and they demonstrate some of the potential of EMG to broader applications. If most movements have a relatively distinct DFT, a neural network or other classifier would be able to differentiate between such movements.

DISCUSSION

Based on the results from testing, the EMG sensor worked well. It was fairly inexpensive to construct, and the parts necessary to build the basic circuit are easy to find. Also, the amplifier's gain is tiny compared to what is required for EEG recording, further simplifying design, and the sensor did not need to be placed inside protective casing. Of course, any consumer product using this technology would need to enclose the sensor in a case, which should improve accuracy by shielding it from noise, but leaving it exposed in these tests demonstrated noise tolerance.

Tests were performed in several locations, but none of them were in a controlled environment. As seen in Fig. 4, the sensor was only implemented on a breadboard, and the exposed wires would have left it open to much more noise than a highly-sensitive system, like an EEG amplifier, could tolerate. These findings are encouraging, since they show that EMG-based interfaces would likely be very noise-tolerant, functioning under many kinds of non-ideal conditions. Because the hardware is also affordable, EMG seems like a promising technology that could precede BCI in consumer-grade applications.

It would be beneficial to explore a few possible improvements to the implemented system, as they could be used to build better EMG devices. Most importantly, the classification accuracy could be improved by building a better feature vector. In these tests, the DFT of a small time window is all that is used. However, in BCI, feature vectors are often constructed using a variety of techniques, and they combine scientific knowledge of human physiology to select the best features [20]. This is a case where EMG technology could benefit from the body of work available for EEG. Likewise, the classification algorithm itself could be improved. Many different ones are employed in BCI, including neural networks [21], and a number of them may also be well-suited to EMG.

The hardware could be improved without much additional cost. Extra filtering could be used for better

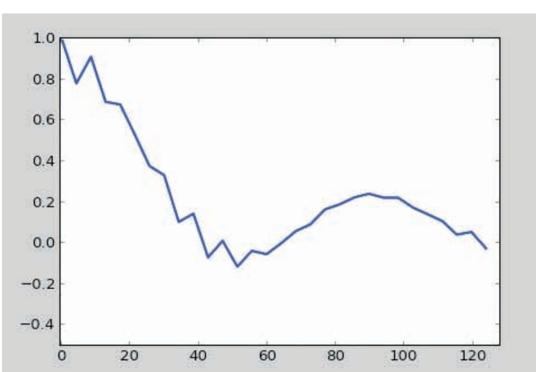

Fig. 6a The typical feature vector of the first classified movement, the continued holding of an outstretched arm

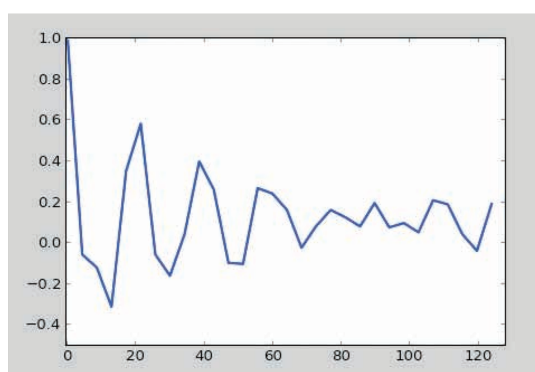

Fig. 6b The typical feature vector of the second classified movement, flexing of the arm

noise reduction. Certain frequencies could be removed if they were not beneficial in a given application. Alternatively, all frequencies could be removed except for a particular bandwidth of interest. As mentioned above, enclosing a soldered sensor in a shielded case would also significantly reduce noise.

It should be noted that the software for interpreting and acting on EMG signals is completely extensible. It was written in python and run on a laptop for this analysis, but it could be written in C for greater speed and run on a standalone processor. If the software were run on a microcontroller like the BLUNO, all of the signal classification could be done wirelessly, and any device paired over an interface like Bluetooth could use that information. For example, an exoskeleton could perform the same action the user is doing by using the interpreted signal from the EMG sensor. Even though this study focused on movement classification, EMG may also be used for movement tracking with the inclusion of some physiological models, as demonstrated in [22]. These improvements could make EMG very well-suited to exoskeletal control.

This analysis is not fully-conclusive. EMG is a broad field, and there is an extensive body of research in the area. There will likely continue to be developments in this subject for many years, along with continuing breakthroughs in EEG and BCI-related topics. However, the results from this cursory study of EMG show that the technology is very nearly ready to expand outside the world of academic research.

To reiterate some of the earlier findings, EMG sensors can be built that are both affordable and able to perform well in varying conditions. BCI is not yet to this point, providing EMG with the opportunity to reach a market that is relatively new and untouched. Even though EMG is not applicable to all of the possible uses of natural interfaces, as BCI would be, it would allow for a number of these applications to be explored with present technology. As evidence of this, note that one of the first EMG-equipped consumer products was very recently announced, the Myo armband [23]. This band allows users to connect to many types of devices wirelessly and control them using EMG. Based on the findings of this analysis, it is likely that more EMG devices will be entering consumer markets soon. This is an exciting technology, and not only will it change how a number of existing technologies function, but it is bound to bring about some new ones that were never before possible.

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