Open Source EMG Device For Controlling a Robotic Hand

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Abstract. Off-the-shelf electronic market is large, diverse and easily accessible by many. Credit card size computers (example: Raspberry Pi) or micro-controller boards (example: Arduino) can be used for learning how to code and how to control embedded systems. Nevertheless, there is a lack of off-the-shelf, open source devices that would enable us to learn about and make use of human signal processing. An example of such a device is an electromyograph (EMG). In this paper we investigated, if an EMG device could fulfill the aforementioned gap. EMG device we used for conducting our experiment was a five channel open source EMG Arduino shield. The performance of the device was evaluated on three healthy male subjects. They were instructed to perform basic finger movements which we classified and executed on the robotic hand. The EMG signal classification was performed using a Support Vector Machine (SVM) algorithm. In our experimental setup the average EMG signal classification accuracy was 78.29%. This we believe demonstrates there are EMG devices on the market today that provide access to cost effective prototyping and learning about EMG signals.

Keywords: open source, electromyograph(EMG), education, support vector machine(SVM), robotic hand

1 Introduction

There are two main groups of people that could benefit from assistive devices such as prosthesis and exoskeletons. First group consist of disabled people as there are more than two million people suffering from limb amputation in USA alone[24]. Although developed countries like USA have a considerable number of disabled people, limb loss is more prevalent in developing countries due to outdated rehabilitation technology, lack off safety precautions and frequent violent conflicts[20]. Prosthesis and other assistive devices would provide much needed tools to achieve a higher quality of life and allow disabled people to perform task previously thought impossible. Exoskeletons we belive would help the second group composed of able bodied men and women working blue collar jobs, as they endure strenuous body positions and movements that can lead to chronic injury. Low-back pain is the leading cause of worker absenteeism after the common cold, accounting for 15% of sick leaves and hundreds of millions of lost work days annually[12]. As we age our motoric skills and capabilities are slowly decreasing. We could increase quality of life by providing body support through wearable devices and stay more independent in old age. We believe that disabled people could benefit from man-machine interfaces in prosthetic devices while healthy men and women could use similar technology in exoskeletons to supports their bodies through strenuous work and old age[23].

Commercial prosthetic devices aimed at helping disabled people are usually designed and made in developed countries. This drives up the cost of such a device and makes for a high economical barrier for people who would benefit from using such devices in their everyday life. Often such companies are not present in markets of developing countries as they focus more on the developed world, where people can afford their products. Here lies an opportunity for prosthetic devices that are cheaper and easier to build. We are also observing an ever bigger population of elderly people who could use added support provided by exoskeletons and similar devices. Our hypothesis is that in order to make your own prototype of an assistive device, most of the building blocks are available as an off-the-shelf component and released under an open-source licence. We tested an open source five channel EMG Arduino Shield[13] for the task of controlling simple finger movements of a 3D printed robotic hand. Using SVM algorithm to classify finger movements, we were able to correctly classify and execute finger movements of a robotic hand with an overall accuracy of 78.29%. We believe our results demonstrate that off-the-shelf open source EMG devices provide sufficient level of performance for their use in the prototyping phase of an exoskeleton device or as a cost effective do it yourself (DIY) prosthetic.

2 Background

Some benefits of open software movement which promotes sharing software with no or minimal restrictions are already observable. It saves money and resources for individuals and companies while providing a foundation that others may build upon[11,5,4,7,10]. In recent years idea the of publishing and freely distributing source material made its way into the hardware world. Nowadays we have 3D printers capable of printing the body a life size robot[8], CNC mills producing printed circuit boards (PCB)[9]. Using Arduino microcontroller addons called **shields** one can make a Geiger counter, air quality sensor, robots[13,7,1]... There has been increasing number of open source projects trying to reverse engineer medical devices[13,3,1,7,6,2]. One such successful project is the Glia stethoscope and oximeter that are verified and used as medical devices in Canada[6]. Quite a few papers published in recent years showcased low-cost robotic limbs and prosthetics[22,21,20,18,16,13]. But to the best of our knowledge none of them used an off-the-shelf open source EMG device.

3 Methods

3.1 Man-machine interface components

A robotic "limb" controlled using EMG signals is made of four main components.

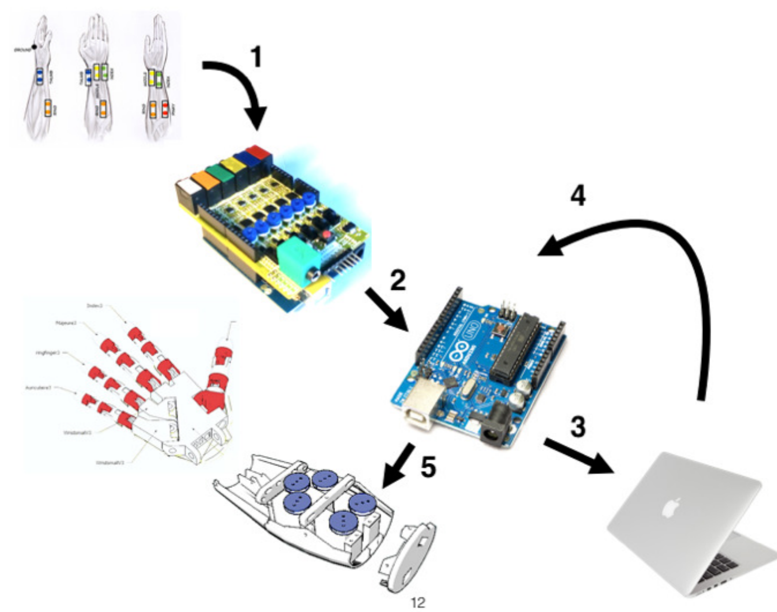

Fig. 1. Hardware components and data flow

Sensor that detects human EMG signals and translates them into digital signals which it sends to a computer. See number 1 and 2 in Figure 1.

Computer that analyses and classifies human signals and sends command to motors. See number 3 and 4 in Figure 1.

Motor that moves the robotic limb. See number 5 in Figure 1.

Body of the robotic limb.

3.2 Task

Subjects were instructed to perform simple finger movements. Starting with an open hand and then bending each finger separately towards the palm and then back to open hand position. They were instructed to perform 60 contractions for each finger with 30 seconds rest after thirty repetitions.

3.3 Signal aquisition

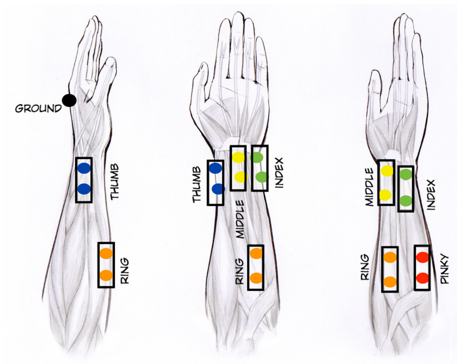

Fig. 2. Electrode placement

Sensors we used to detect electrochemical signals of the muscles were five passive bipolar disposable silver chloride electrodes. These electrodes are cost effective and easy to use. They are pre-gelled, adhesive, non-invasive and do not cause contamination. We used guidelines suggested by [13] in placing the electrodes. Electric signal detected by the electrodes is amplified 1000 times by the EMG shield. The recording frequency was 500 Hz per channel when five EMG channels were used.

3.4 Pattern recognition

Signal analysis software was written using Open Frameworks, a collection of open-source C++ libraries. We filtered the raw EMG signal by applying a root mean square (RMS), low pass filter and peak detection. We applied the SVM algorithm to the filtered signal for classification purposes.

Low Pass filter: The input is the raw signal on which we perform RMS to extract the amplitude of the EMG signal. It averages successive samples gathered in a 15 millisecond time window. We used a 15 millisecond time window as that was sufficient to smooth out the RMS signal.

Peak detection: Time and gradient based peak detector was used as suggested in [19]. Peak detection filter scans the incoming signal for samples that are larger than all the other samples within the time window, while all previous samples must have a positive slope and all the following ones must have a negative slope. Time window for collecting the sample was 15 milliseconds.

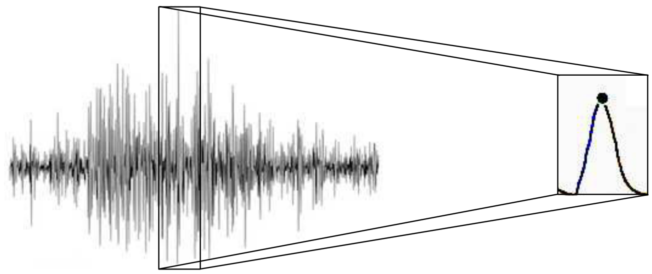

Fig. 3. Raw signal filtering and peak detection

Support Vector Machine: SVM classification was performed using the dLib open-source library[4]. There were 120 samples collected per finger movement class. Collected samples were devided into 100 samples for supervised learning with SVM and 20 samples to be used for classification accuracy testing. The dominant approach for using SVM for a multiclass problem is to reduce the single multiclass problem into multiple binary classification problems. If N possible classes are used then N binary classifiers are trained which are then used to vote on the identity of a test sample. Common method for such reduction include building binary classifiers which distinguish between one of the labels and the rest using a so called one-versus-all approach. Classification of new instances for the one-versus-all case is done by a winner-takes-all strategy. The classifier with highest output function assigns the class[4]. This is the approach used for our SVM classification algorithm. Once classification has been performed, computer software sends a command to Arduino which forwards the command to servo motors.

3.5 Robotic Arm

We 3D printed the robotic arm parts[8]. Robotic arm we printed had five degrees of freedom. We used five servo motors and each servo motor was attached (through a nylon string), to the end point of a finger on the robotic hand. When computer software decoded a finger movement, it sent a command via USB serial port to the Arduino that controled the servo motors which in turn moved the fingers of the robotic hand.

4 Results and Discussion

We collected 120 samples per finger movement, which were then divided into 100 samples for supervised learning with SVM and 20 samples to be used for accuracy testing of each finger movement. Looking at the data collected from subjects that had smaller forearms we saw the accuracy of classification diminish, as there is more cross-over noise picked up by the electrodes. This is something that must be taken into account if we would like to use such a device for small children or

Table 1. Finger classification accuracy in percentages

	Thumb	Index	Middle	Ring	Pinky
Subject 1	82.23	74.98	73.67	75.45	81.31
Subject 2	84.31	78.43	72.92	74.18	83.33
Subject 3	80.22	77.92	82.15	72.63	80.64

people with smaller, thinner forearms. Another observation was that accuracy also deteriorates with less isolated fingers such as middle and ring finger. Thumb finger movement classification accuracy was 82.25% and pinky finger movement classification accuracy was 81.76%. Less isolated(in terms of muscle density) index finger 77.11% , middle finger 76.24% and ring finger 74.08% classification accuracy is significantly lower. This we conclude is also due to crossover noise between many muscles that operate the hand movements as their signal EMG signals are hard to filter.

Feature extraction from the signal was performed using simple filters and algorithms as research suggests that in order to achieve reliable and proportional control we do not need high accuracy in mapping EMG and kinematics[17]. Although there are plenty of papers which use more complex optimization algorithms and achieve bigger accuracy in a controlled lab environment[22]. Respectfully, data collected during a carefully supervised lab setting does not represent a real life scenario where our EMG signal classifier software must relearn quickly as EMG signals change over time under the influence of various factors (new movement, electrode dislocation, noise, etc.), deteriorating control performance. It is therefore necessary to regularly retrain a new model[14]. Gijsberts et al. in their paper published in 2014 used an Incremental Ridge Regression and an approximation of the Gaussian Kernel known as Random Fourier Features combined to predict finger forces from EMG signals. Their approach resulted in that the subjects could reliably grasp, carry and release everyday-life objects, irrespective of the signal changes even during movement previously untrained for as the algorithm could quickly retrain itself[15]. As computing is a much cheaper resource with todays technology, this suggest that even with lower quality sensors but effective EMG signal analysis we can achieve reliable performance. The ability of EMG analysis software to relearn quickly is more important that using a high accuracy classification algorithm which cannot classify a signal untrained for. The EMG we tested is not a research grade device nor does it claim to be one. Among quite a few limitations an important one is the data acquisition frequency, which would optimally be at least 1 kHz, is in our case limited to 500 Hz while using five EMG channels. Previously mentioned limitation is caused by the Arduino maximal bit-rate transfer speed and number of EMG channels we are using. In the future we would like to work on redundancy and reliability as indicated in [15,17] considering reliability is one of the most important factors we must consider if we want our users to accept our devices in their everyday life scenarios.

5 Acknowledgment

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