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A Comparison of Supervised Learning Algorithms for Telerobotic Control Using Electromyography Signals

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Abstract

Human Computer Interaction (HCI) is central for many applications, including hazardous environment inspection and telemedicine. Whereas traditional methods of HCI for teleoperating electromechanical systems include joysticks, levers, or buttons, our research focuses on using electromyography (EMG) signals to improve intuition and response time. An important challenge is to accurately and efficiently extract and map EMG signals to known position for real-time control. In this preliminary work, we compare the accuracy and real-time performance of several machine-learning techniques for recognizing specific arm positions. We present results from offline analysis, as well as end-to-end operation using a robotic arm.

Introduction

In certain applications of telemedicine or telerobotic control, the speed of communication between human and computer controller is vital to the function of the system. Intuitive controllers that map human actions to control signals can improve real-time performance, as well as decrease requisite training. Our research focuses on exploiting electromyography (EMG) signals for telerobotics.

An important challenge is to map EMG inputs to control signals. While our goal is human-controlled, fluid motion across a variety of telerobotic applications, this preliminary work focuses on how to recognize static arm positions accurately and efficiently for real-time control. We made use of EMG surface electrodes for the bicep, tricep, anterior deltoid, and posterior deltoid muscles, and these EMG signals are analyzed to determine the position of the elbow and shoulder, each about their axis of rotation. Given these continuous positions, we evaluated a suite of supervised learning approaches for classifying arm state, comparing each algorithm's accuracy and efficiency. We also demonstrate end-to-end operation using a robotic arm.

Prior work was either entirely in simulation (Al-Faiz, Ali, and Miry 2010), or just tested a single learning model, such as a neural network (Hiraiwa, Shimohara, and Tokunaga 1989) or via dimensionality reduction (Fukuda et al. 2003). By contrast, our study compares several algorithms, including naïve Bayes, decision trees, instance-based search, support vector machines (SVM), and logistic regression.

Position sensors have been utilized to determine position and direction of movement (Artemiadis and Kyriakopoulos 2007). Our study attempted to classify static positions as a method for determining position and potentially direction of dynamic movements; if this approach is shown to be feasible for active motion, then less subject-mounted hardware would be required.

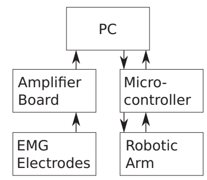

Figure 1: System overview

System Design

Refer to Figure 1 for a visual overview of our system. A NeuroFieldz (Boston, MA) prototype board acquires and amplifies action potentials from EMG electrodes and sends the data to a PC (T440p Lenovo 4, Core i7-4700MQ 2.4GHz, 8GB RAM), which preprocesses the data and applies the learning model to output control signals via a microcontroller. A PhantomX Reactor Research Robot Arm Kit was used to evaluate end-to-end behavior.

Data Collection

EMG signals were measured at three positions for one subject (the mean absolute voltage of each data point was taken over twenty seconds, 1000 samples per second): (1) the right elbow at a 90°angle, so the wrist was perpendicular to the body; (2) the right elbow at a 150°angle, so the wrist was perpendicular to the body; (3) the right elbow at a 100-110°angle, so the wrist was perpendicular to the body.

The positional feedback capability of the Dynamixel AX-12A robotic actuators was used to provide training outputs

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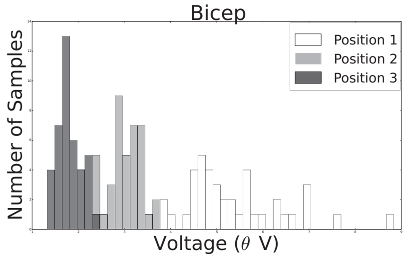

Figure 2: Histogram of the Bicep mean absolute value for the three positions

	NB	SVM	LR	kNN	J48	RF
Accuracy (%)	90.0	95.7	90.1	97.8	95.1	97.3
Training (ms)	0	20	30	0	20	120
Testing (ms)	0.02	0.15	0.03	0.08	0.02	0.02

Table 1: Evaluation results with naïve Bayes (NB), support vector machines (SVM), logistic regression (LR), k-nearest neighbor (kNN), J48, and Random Forests (RF).

for the learning algorithms. While recording EMG signals, the robotic arm was moved into an analogous position to the right arm of the subject.

Preprocessing

The components of EMG signals that are useful for analysis are lower than 400Hz, with the dominant section between 50 – 150Hz. The lower frequencies, below 20 Hz, were filtered out because (a) the signal voltage was superimposed on a DC component and (b) motion artifacts. Thus, once the data was collected, a band-pass filter with a lower frequency cutoff of 50Hz and an upper cutoff of 400Hz was used to removed the DC components as well as some noise. Additionally, the samples of EMG readings were rectified. Finally, the mean absolute value of each of the four muscles was calculated and used as an attribute for training/testing sets. We hypothesized that given a relatively clean signal, a supervised learning algorithm would learn to generalize over remaining sources of noise.

Supervised Learning

Before comparing supervised learning algorithms, we plotted the mean voltage for each muscle corresponding to each position. The bicep (Figure 2) and the anterior deltoid show clear distinctions, leading us to hypothesize that the three static positions could be distinguished.

Each supervised learning algorithm makes modeling assumptions, and thus the goal of this study was to evaluate a variety of approaches, comparing both accuracy and training/testing time. For this application we evaluated naïve Bayes, support vector machine (radial basis function kernel), logistic regression, k-nearest neighbors (kNN; L2 distance, $\frac{1}{d}$ weighting), J48 decision trees, and Random Forests. We conducted 10-fold cross validation across 369 instances using Weka v3.6, with results summarized in Table 1.

We found that all the algorithms correctly classified operator position with at least 89% accuracy. kNN ($k = 4$; we evaluated k values 1–10) yielded the greatest accuracy ($> 97\%$) with virtually no training time. Random Forests had similar accuracy, but required 120ms for training.

For real-time control it is critical that model prediction takes no longer than 50 milliseconds. For this relatively small dataset, all of the algorithms far surpassed this requirement, requiring less than 1 millisecond on average.

Discussion

Based on the results of the algorithmic evaluation, kNN was selected and a single operator was successfully able to control the robotic arm using static arm positions.[1] This is important because static positions can be used alongside dynamic movements to help determine the direction of movement using only action potentials from the EMG recordings.

All of the algorithms were fast enough for real-time control, but kNN and Random Forests were qualitatively more accurate. Unfortunately, the kNN algorithm becomes slower with an increased training set size. We intend to explore Boundary Forests (Mathy et al. 2015) as an online variant that will maintain accuracy and efficiency over time. A pitfall of Random Forests is that they are classically trained offline, which limits their usefulness in this context – we plan to evaluate more recent online variants (Saffari et al. 2009).

Following algorithmic improvements, we plan to evaluate whether the system design generalizes to multiple subjects, and additional static positions, with the eventual goal of continuous motion.

References

Al-Faiz, M. Z.; Ali, A.; and Miry, A. H. 2010. A k-nearest neighbor based algorithm for human arm movements recognition using EMG signals. In *Energy, Power and Control (EPC-IQ)*, 159–167.

Artemiadis, P. K., and Kyriakopoulos, K. J. 2007. EMG-based position and force control of a robot arm: Application to teleoperation and orthosis. In *Advanced Intelligent Mechatronics*, 1–6.

Fukuda, O.; Tsuji, T.; Kaneko, M.; and Otsuka, A. 2003. A human-assisting manipulator teleoperated by EMG signals and arm motions. *IEEE Transactions on Robotics and Automation* 19(2):210–222.

Hiraiwa, A.; Shimohara, K.; and Tokunaga, Y. 1989. EMG pattern analysis and classification by neural network. In *Systems, Man and Cybernetics*, 1113–1115.

Mathy, C.; Derbinsky, N.; Bento, J.; Rosenthal, J.; and Yedidia, J. S. 2015. The boundary forest algorithm for online supervised and unsupervised learning. In *Proceedings of the 29th AAAI Conference on Artificial Intelligence*, 2864–2870.

Saffari, A.; Leistner, C.; Santner, J.; Godec, M.; and Bischof, H. 2009. On-line random forests. In *Computer Vision Workshops (ICCV)*, 1393–1400.

[1] See: http://tmfrasca.info/emgrobotcontrol/