EMG Based Demonstrations as a Tool for Robot Learning

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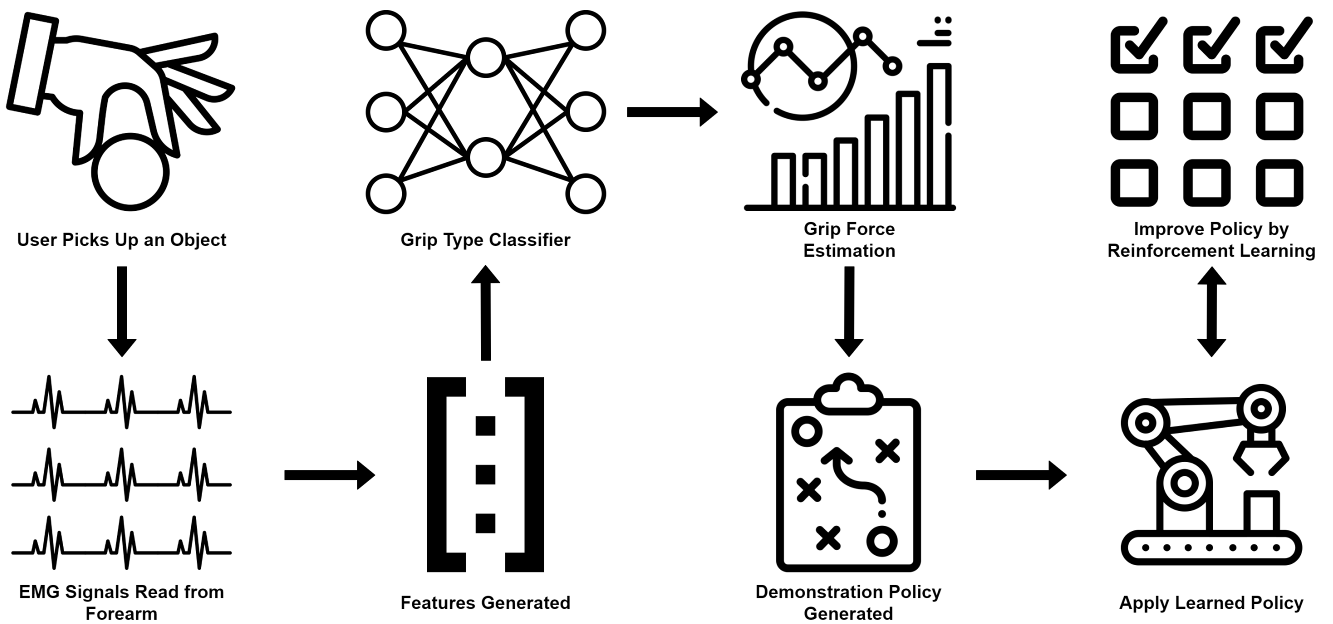

Figure 1: Main System Overview

ABSTRACT

This paper outlines an approach for using Skin Surface Electromyography (EMG) as a means for human demonstration of object manipulation. A classifier and multiple regression models are used to infer the grip type and force magnitude from the EMG data. A Reinforcement Learning Agent learns to map these to the robot's grip type and force actuators by finding near-optimal actions for the initial demonstrations by beginning exploration from the initial estimated policy.

After several such demonstrations, the robot is expected to establish a good mapping from demonstrations to near-optimal actions and then can be expected to learn to manipulate unknown objects after a single human demonstration.

(This project is being conducted as the author's Senior Honors Thesis for Bachelors in Computer Science.)

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CCS CONCEPTS

• **Human-centered computing** → **Collaborative interaction**; **Gestural input**.

KEYWORDS

Human-Robot Collaboration, Skin Surface Electromyography, Object Manipulation, Learning by Demonstration, Reinforcement Learning

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1 INTRODUCTION

It is challenging for robots to manipulate unique or unknown objects where characteristics such as weight, deformability, surface friction and fragility can not be inferred from mere vision or any other passive sensory approaches but are necessary to plan a good approach.

Since the possible action space is large and the cost of exploring might be high, a lot of work has been done in informing robot policies by using human demonstration [1][3][5][7].

However, it is difficult to establish a single mapping from human demonstration to robot action because the anatomical characteristics and personal preferences differ for each individual human demonstrator. The system purposed in this paper approaches this issue by maintaining a policy that defines the mapping between human demonstrations and robot actions. The policy starts from an estimate but as the robot explores the object, it is able to improve the policy by discovering better actions (less force, more successful grip type) corresponding to the demonstrations. As a result, the robot is able to adapt and compensate for the particular style of the demonstrator.

2 PRIOR WORK

I was a Software Engineering Intern at CTRL Labs past summer where I worked on mapping EMG-based control schemes to a hexapod robot to play soccer. Previously, I designed and developed an Augmented Reality Interface for robots that I presented as a Late Breaking Report in HRI 2019 and was also a part of the lab's winning proposal for Verizon 5G EdTech Challenge.

3 METHODOLOGY AND APPARATUS

The EMG signals will be obtained using CTRL Kit. It is a wireless, 16-channel, 200Hz, dry-electrode EMG-band. A 2-Finger Robotiq Gripper attached to a UR5 arm would be used as the robot manipulator. The learning apparatus would consist of a series of tennis balls filled internally to have varying total weights. This would be performed on a crafted auto-resetting bed where the ball would automatically roll to the initial position if the task of gripping, picking, moving and placing fails.

4 EMG SIGNAL COLLECTION AND FEATURIZATION

The process begins with a calibration step. EMG signals using different grip types and at varying force levels are collected. The force levels are established by using a linear-force sensor. This data is used to train a classifier for Grip Types and multiple regression models for force corresponding to each grip type.

To facilitate the classifier and regression models, EMG data is featurized for their input. Multiple studies [4] [8] [9] [10] [11] have identified good features to use for these tasks and a pool of features would be selected and implemented from among them.

5 GRIP TYPE CLASSIFICATION AND FORCE ESTIMATION

In general, grip types can be identified by the relative activation of different muscles and the temporal sequence of activation leading up to the grip [6], therefore the pool of features provided to the classifier would be designed to deliver this information.

On the other hand, force can be estimated much simply by the activation intensity of the muscles. Different grip types would correspond to different weightage to these intensities in establishing the overall force and therefore regression models would be generated corresponding to each grip type using the relevant features from the calibration data [2].

6 DEMONSTRATION POLICY GENERATION

The Demonstration Policy aims to establish the mapping:

$$(G_H, F_H) \rightarrow (G_R, F_R)$$

where G_H is the human grip type used in the demonstration, F_H is the estimated force from the demonstration, G_R is the optimal grip type for the robot to use and F_R is the optimal force required.

In our case, the robot has only two digits and is only capable of a single type of grip. Therefore, it must learn to adapt different kinds of human grip types to that particular grip type.

Initially, a naive policy is established:

$$(g, f) \rightarrow (TwoDigitGrasp, f)$$

which maps any grip type to the robot one by suggesting the same force.

7 POLICY EXECUTION AND IMPROVEMENT

The robot explores the object and establishes the minimum force needed to grip the object, pick it up and move it using Reinforcement Learning. This exploration is guided and by and is used to improve the Demonstration Policy.

After several demonstrations, the agent is expected to adapt to the particular style of the demonstrator as well as compensate for slight errors in grip classification and force estimation. From there on, it can be expected to handle unknown objects at near optimal levels using a single human demonstration.

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REFERENCES

[1] Staffan Ekvall and Danica Kragic. 2004. Interactive grasp learning based on human demonstration. In *IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA'04. 2004*, Vol. 4. IEEE, 3519–3524.

[2] Marco JM Hoozemans and Jaap H Van Dieen. 2005. Prediction of handgrip forces using surface EMG of forearm muscles. *Journal of electromyography and kinesiology* 15, 4 (2005), 358–366.

[3] Haiyang Jin, Qing Chen, Zhixian Chen, Ying Hu, and Jianwei Zhang. 2016. Multi-LeapMotion sensor based demonstration for robotic refine tabletop object manipulation task. *CAAI Transactions on Intelligence Technology* 1, 1 (2016), 104–113.

[4] Zhaojie Ju, Gaoxiang Ouyang, Marzena Wilamowska-Korsak, and Honghai Liu. 2013. Surface EMG based hand manipulation identification via nonlinear feature extraction and classification. *IEEE Sensors Journal* 13, 9 (2013), 3302–3311.

[5] Alex X Lee, Abhishek Gupta, Henry Lu, Sergey Levine, and Pieter Abbeel. 2015. Learning from multiple demonstrations using trajectory-aware non-rigid registration with applications to deformable object manipulation. In *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 5265–5272.

[6] Jaime Martin-Martin and Antonio I Cuesta-Vargas. 2014. Quantification of functional hand grip using electromyography and inertial sensor-derived accelerations: clinical implications. *Biomedical engineering online* 13, 1 (2014), 161.

[7] Peter Pastor, Heiko Hoffmann, Tamim Asfour, and Stefan Schaal. 2009. Learning and generalization of motor skills by learning from demonstration. In *2009 IEEE International Conference on Robotics and Automation*. IEEE, 763–768.

[8] Angkoon Phinyomark, S Hirunviriya, C Limsakul, and P Phukpattaranont. 2010. Evaluation of EMG feature extraction for hand movement recognition based on Euclidean distance and standard deviation. In *ECTI-CON2010: The 2010 ECTI International Confernce on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology*. IEEE, 856–860.

[9] Angkoon Phinyomark, Rami N Khushaba, and Erik Scheme. 2018. Feature extraction and selection for myoelectric control based on wearable EMG sensors. *Sensors* 18, 5 (2018), 1615.

[10] J Rafiee, MA Rafiee, F Yavari, and MP Schoen. 2011. Feature extraction of forearm EMG signals for prosthetics. *Expert Systems with Applications* 38, 4 (2011), 4058–4067.

[11] Christopher Spiewak, MdRasedul Islam, Md Assad-Uz Zaman, Mohammad Habibur Rahman, et al. 2018. A Comprehensive Study on EMG Feature Extraction and Classifiers. *Open Access Journal Of Biomedical Engineering And Biosciences* 1, 1 (2018), 17–26.