Towards Sonomyography-Based Real-Time Control of Powered Prosthesis Grasp Synergies

Keshav Bimbraw, Elizabeth Fox, Gil Weinberg, and Frank L. Hammond III, *IEEE Member*

***Abstract*— Sonomyography (ultrasound imaging) offers a way of classifying complex muscle activity and configuration, with higher SNR and lower hardware requirements than sEMG, using various supervised learning algorithms. The physiological image obtained from an ultrasound probe can be used to train a classification algorithm which can run on real time ultrasound images. The predicted values can then be mapped onto assistive or teleoperated robots. This paper describes the classification of ultrasound information and its subsequent mapping onto a soft robotic gripper as a step toward direct synergy control. Support Vector Classification algorithm has been used to classify ultrasound information into a set of defined states: open, closed, pinch and hook grasps. Once the model was trained with the ultrasound image data, real time input from the forearm was used to predict these states. The final predicted state output then set joint stiffnesses in the soft actuators, changing their interactions or synergies, to obtain the corresponding soft robotic gripper states. Data collection was carried out on five different test subjects for eight trials each. An average accuracy percentage of 93% was obtained averaged over all data. This real-time ultrasound-based control of a soft robotic gripper constitutes a promising step toward intuitive and robust biosignal-based control methods for robots.**

I. Introduction

Multiple techniques have been employed in the past in an attempt to capture muscle movement, muscle activation, and general human intent to move specific body parts. Despite its limitations, surface Electromyography (sEMG) has been among the most widely used technologies for control of prostheses and powered orthoses [1]. Multiple electrodes can be used to classify a large set of hand posture states, but it might be impractical for users to have a number of electrodes placed at several points on their arms [2]. Even with developments in signal processing, issues like latency and noise reduction inhibit more human-like control of prostheses and orthoses [3]. Considering these clear sEMG limitations, sonomyography (ultrasound imaging) has been explored as an alternative sensing modality that can capture both muscle configuration and movement [4], [5], [6].

Keshav Bimbraw was a graduate student in the Robotic Musicianship Laboratory at Georgia Institute of Technology, Atlanta, GA, 30332 USA.

Elizabeth Fox is a graduate student working in the Adaptive Robotic Manipulation Laboratory, in the George W. Woodruff School of Mechanical Engineering at Georgia Institute of Technology, Atlanta, GA, 30332 USA.

Gil Weinberg is a professor in the Georgia Tech School of Music and the founding director of the Georgia Tech Center for Music Technology, Atlanta, GA, 30332 USA.

Frank L. Hammond III is an Assistant Professor in the George W. Woodruff School of Mechanical Engineering and Wallace H. Coulter Department of Biomedical Engineering with Georgia Institute of Technology, Atlanta, GA, 30332 USA `frank.hammond@me.gatech.edu`

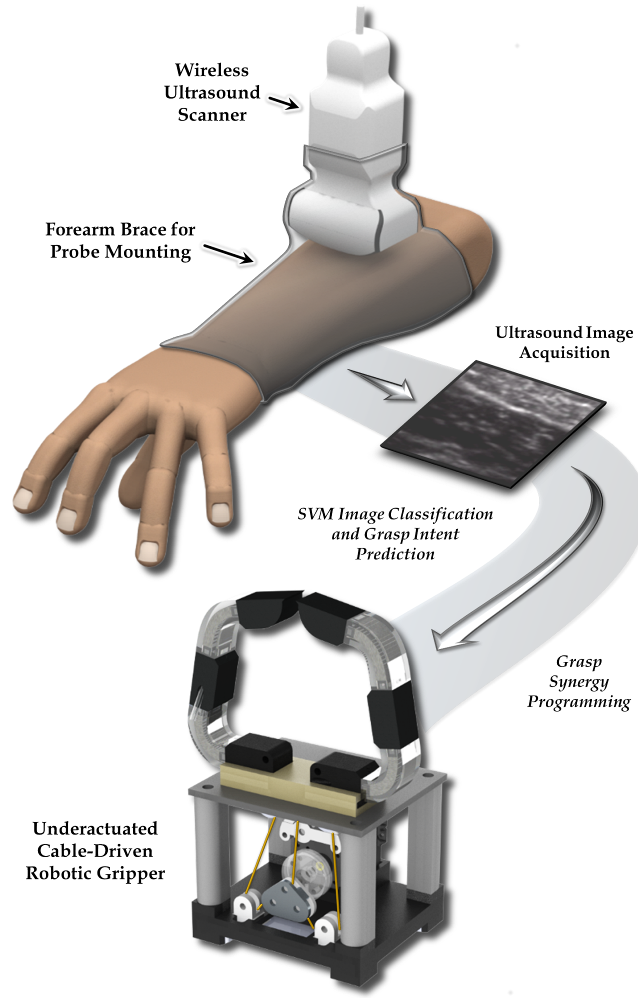

Fig. 1. Illustration of the proposed system for sonomyography-based hand configuration identification and robotic hand synergy selection.

Sonomyograpy has been shown to be capable of identifying different gestures and finger movements by analyzing the image obtained from ultrasound data with a combination of current image processing and classification algorithms [7]. Several groups have used ultrasound imaging to distinguish fine hand movements with an accuracy of over 90 percent [8], [9]. In this implementation, the ultrasound probes captured the needed data from just one location on the forearm unlike EMGs which require multiple electrodes to achieve similar accuracy. The possibility of having a lower profile device opens the possibility of developing a sensing modality that is portable while providing dexterous control capabilities to prostheses and orthoses. Only recently has ultrasound imaging been used as a means for controlling an external

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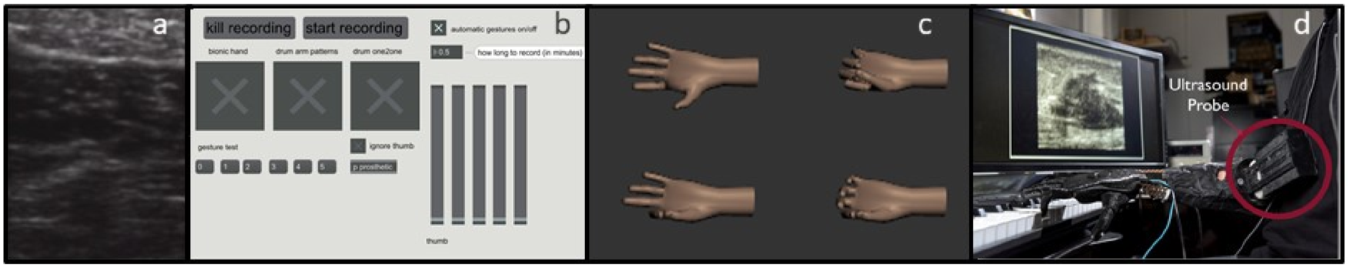

Fig. 2. Data collection and execution process - (a) The ultrasound image obtained from the forearm, (b) Max/MSP interface used to capture data and train algorithm, (c) Animation with desired hand configurations, (d) Full system setup with probe and wearable robot prosthesis.

device [4], [10], [11], [12], [13].

Ultrasound is a promising method for the classification of many different hand motions. Using various machine learning algorithms as in [4], [10], [11], [12], [9], sonomyography can produce reliable results despite issues with localization and probe movement. This paper describes the implementation of sonomyography for control of a soft robotic gripper. Specifically, we wish to use sonomyography to implement direct postural synergy control, which has been shown [14], [15], [16] to be the method by which the human brain controls its hands, and to have a significant dimensional reduction of control inputs. To achieve this, real-time ultrasound images from the forearm are classified using Support Vector Classification algorithm into four different hand configurations. The predicted values are then mapped onto a the joints of an underactuated robotic gripper with secondary joint mechanisms that allow for direct synergy control, enabling the creation different grasp types important for the execution of ADLs. The ability to change grasp types represents an improvement in capabilities over other single-actuator hands and could potentially increase the range of objects that can be grasped. In this paper, section II describes the data collection process, classification algorithm, design and control of the soft robot. In section III, the methodology is discussed. Results are presented in section IV with conclusions in section V.

II. Data Collection, Algorithm, and Control

Figure 1 shows the different components of the system; an ultrasound scanner is affixed to a human forearm and wirelessly trasmits the images to the computer, which classifies the ultrasound images and uses that data to control the robotic gripper. This section goes into detail about the different components of the setup.

A. *Data collection for sonomyography*

To obtain user input, ultrasound images were obtained from the forearm using a Uprobe series Sonostar wireless ultrasound scanner (Sonostar Technologies Co., Limited, Guangzhou, China). A forearm brace was used to mount the ultrasound probe and prevent slip. The ultrasound data were displayed on WirelessUSG application on an Android device as shown in Figure 2(a), then transferred to a laptop.

B. *Data Classification Algorithm*

The images from the ultrasound were analyzed in order to obtain useful data. Support Vector Machine (SVM) algorithm was used because of its ease of implementation and effectiveness for image classification problems. SVM is a supervised learning algorithm used for both classification and regression and has proven particularly effective in image classification tasks. The classification is done by finding the hyper-plane

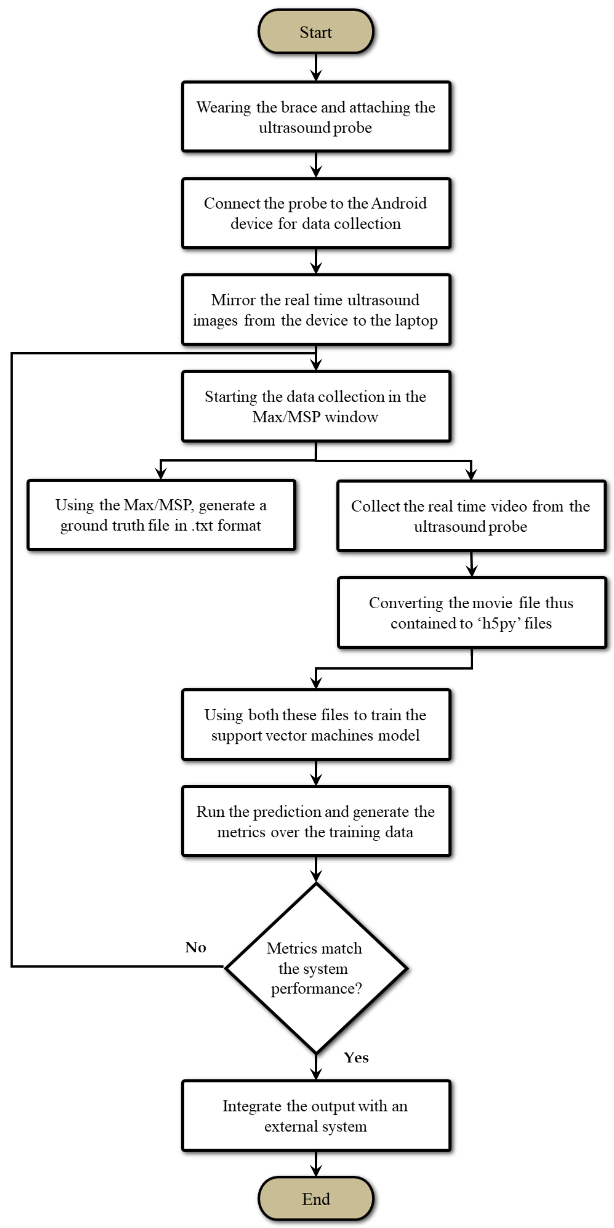

Fig. 3. The control diagram of the Ultrasound/SVM.

that can best differentiate the classes, with the performance measured in terms of various, task-specific metrics. Scikit learn is an optimized machine learning library for python in which the sklearn.svm.svc class has been used for the classification class. More information about this library can be found here [17].

Figure 2 shows the components of the training and date collection process for the SVM, and Figure 3 details the full process to classify the ultrasound data in real time and output it to an external device. One data collection trial involved collecting the hand configuration change data for 30 seconds. Figure 2(b) shows the interface for data collection and training set up in Max/MSP software. This interface captures the ultrasound data as it is displayed on the laptop. During this 30 second data collection period, the different hand configurations were cyclically indicated using Max/MSP interface as shown in Figure 2(c). In this project, four different hand configurations were considered corresponding to the data that needed to be trained. In clockwise order from the top left of Figure 2(c), they were: open hand, closed hand, pinch and hook configurations.

The data collected in this 30 second period was used to train the machine learning model after pre-processing. Metrics obtained from test data provided a good estimate of system performance. If the metrics indicated the model accuracy was less than 90 percent, it indicated errors in collected data that consequently lead to bad system performance. Once the machine learning model was trained based on the data, it was able to execute real time prediction of different hand configurations. Figure 2(d) shows one such implementation wherein the output of the prediction of the machine learning model was used to actuate different components of a robotic prosthetic hand and play the piano.

C. The Soft Robotic Gripper

A soft robotic gripper was designed to emulate a simplified function of the human hand for the purpose of grasping objects and mimicking the hand configurations using direct synergy control. The gripper was underactuated, which allowed it to automatically conform to the object shape, balance forces, and be low cost, low weight, and have simpler control implementation. Despite its simplicity, it is possible to control its pre-grasp configuration and motion patterns before grasp acquisition. The soft gripper is comprised of two two-phalanx fingers in a cable driven underactuated system. Joint flexures can be pneumatically stiffened, which changes joint motion as cable-tendons are pulled. This ability to adjust joint stiffness is a direct implementation of synergy control and increases the versatility of the grasp shape compared to typical underactuated hands, which have a limited, if not one, set of pre-grasp configurations.

The soft robotic links are attached to a 3D printed base with a Dynamixel AX-12-A servo motor used to flex the grasper joints. The floating pulley/whiffle tree transmission mechanism is based on the Yale OpenHand design [18]. Figure 4 shows a rendering of the soft robotic gripper.

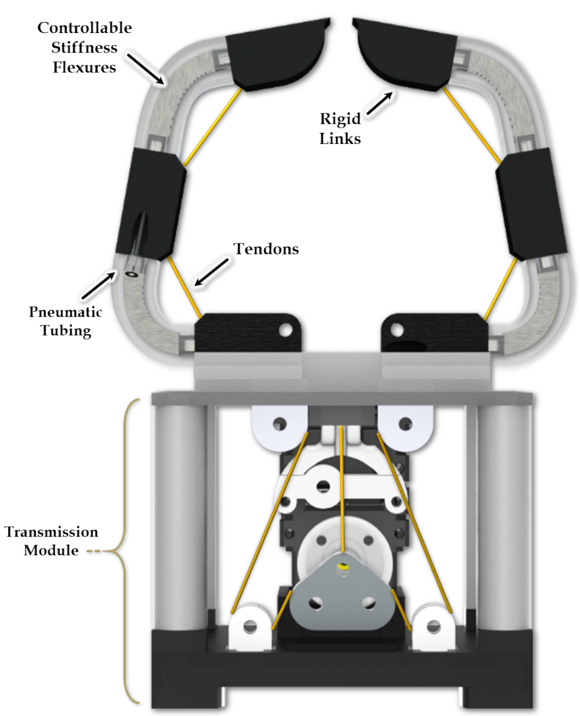

Fig. 4. A rendering of the soft robotic gripper. The base and Dynamixel motor are rendered in grey; the transmission components from the Yale OpenHand are rendered in off-white; the tendons are in orange; the rigid finger segments in black; and the controllable-stiffness flexures in light grey.

D. Control of the Soft Robotic Gripper

The soft gripper had its own mid-level controller commanded by the output of the SVM; the full setup schematic is shown in Figure 5. The SVM model specified the grasp type in the form of an integer from 0 to 3. The microcontroller then mapped the SVM output to the corresponding joint pressures, which were then set by an Arduino-based pressure regulation platform. The soft elements of the gripper made it difficult to achieve the required grasp shapes due to errors in the actuator pressure levels. A control board was used to correct the joint pressures and achieve the desired hand posture. Once joint pressure values were within an acceptable range, the Dynamixel AX-12 servomotor was activated to close the gripper until it either reached the predetermined maximum torque or the tendon length limit. As the grasp type information predicted by the ultrasound SVM algorithm changed, the corresponding joint pressure values changed as well. The gripper was re-opened and the process in Figure 5 repeated to achieve the different robotic gripper postures. The four different hand configurations from the training data correspond to four different end gripper configurations as shown in Figure 6.

III. Results and Discussion

This section discusses the various metrics calculating the accuracy of the ultrasound controller. An overall accuracy percentage of 93% was obtained, averaged over all test subjects and trials.

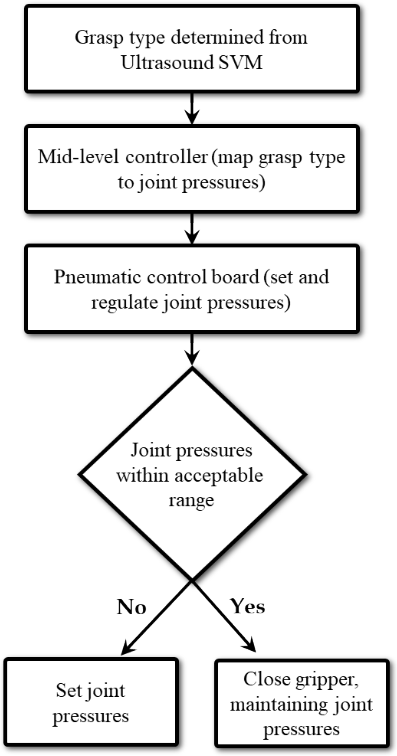

Fig. 5. A diagram of the control algorithm used to select different soft robotic gripper states and grasping actions based upon ultrasound data.

A. *Human Subject Recruitment*

Five volunteers were recruited for the human subject study and data collection. This was a study approved by the Georgia Tech Institutional Review Board (IRB).

B. *Evaluation Metrics*

For the SVM, a classification report was generated which indicates the precision, recall, F-1, support scores and confusion matrix. Confusion matrices indicated how close to expected results were the actual algorithmic predictions. Figure 7 shows confusion matrices for two different trials.

C. *Accuracy over test data*

Metrics were obtained for the eight trials. An average accuracy percentage of 93.5% over the testing data was obtained, averaged over eight trials for one of the test subjects. Figure 8 shows the average accuracy percentages over eight trials for one of the test subjects. An overall accuracy percentage of 93% was observed over 8 trials per test subject.

D. *Issues and future work*

There are several potential areas of improvement. Low changes in joint bending stiffness were observed due to the nature of granular jamming and limits of vacuum pressure. Friction on the cable within the joints, compounded at high bending, was high compared to actuation forces and thus had a significant impact. Interference from the pneumatic tubing to the joints reduced performance and added increased variability to the system. For certain trials, even with high accuracy percentages, the actual predictions of the machine learning model were not as accurate. This was because of overfitting, which is a major issue in supervised learning for image classification. Feature extraction on ultrasound images as opposed to using just the raw ultrasound image data seems to be a potential avenue for research to reduce overfitting and

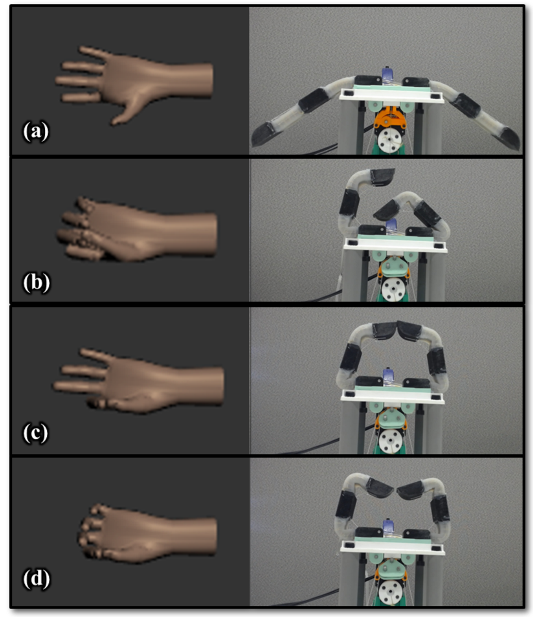

Fig. 6. Different hand configurations and the corresponding soft robotic gripper states. (a) Open hand configuration, (b) Closed hand configuration, (c) Pinch configuration and (d) Hook configuration..

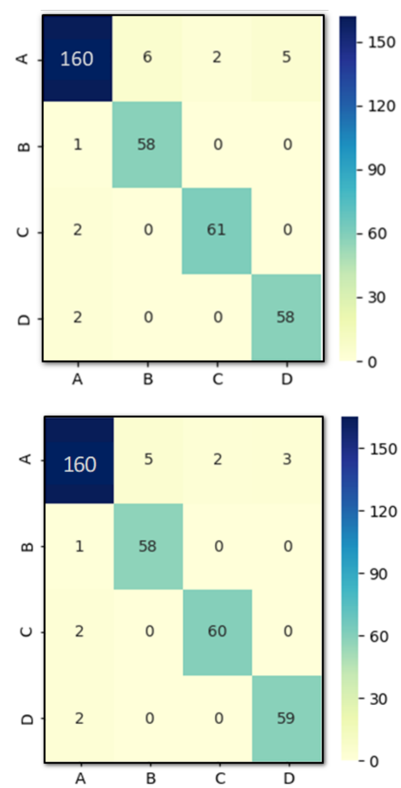

Fig. 7. The confusion matrices for two different trials for a test subject. The letters along the axes correspond to the following configurations: A: open hand, B: closed hand, C: pinch and D: hook.

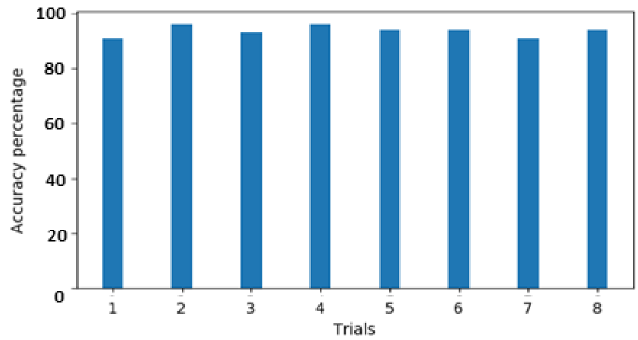

Fig. 8. Accuracy percentage over eight trials for one test subject.

improve accuracy of the predictions. Improving the quality of data collection can also improve classifier performance.

IV. Conclusion

We described the control of a soft robotic gripper through values predicted by our machine learning model. Real time ultrasound images and a custom interface was used to train a model. Support Vector classification method was used, and the predicted values were sent over a serial port to the Arduino-based system used to control pressure states in a soft robotic gripper. We were able to successfully develop the interface and get an overall accuracy percentage of 93% over five test subjects, with eight trials each. The current system can be improved in several ways in terms of soft robotic flexure stiffness and overfitting when it comes to training the model. Overall, this work presents a promising biosignal based control of a robot for applications ranging from control of assistive robots to teleoperated robots.

Acknowledgments

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