# Data Driven Actuator Selection

## Project Progress Report

Divyanshu Pabia

RA2111003011373

# Nomenclature

SVM:  Support Vector Machines

NN: Neural Networks

RBF: Radial basis Function

GAN: Generative Adversarial Network

# Contents

# 1. Introduction

## 1.1 Conventional Robots and need of artificial muscles:

Conventional robots are based on rigid materials for actuation and load bearing. They certainly were not designed to be low cost, safe near people and adaptable to unpredictable challenges. Hence, human-robot and robot–environment interactions must be monitored and precisely controlled to avoid safety hazards to humans or the robot.

We've made good progress with robots' brains, but their bodies are still primitive. In contrast to conventional robots, human bodies extensively use soft and deformable materials such as muscle and skin. We need a new generation of robot bodies inspired by the elegance, efficiency, and soft materials of the designs found in nature. Soft robotics is a new field of research in this idea. Biological muscles have evolved to become what we see today - they can contract fast enough to power the high-speed wings of birds, are strong enough to move elephants and are highly versatile as in the arms of an octopus.

## 1.2 What are actuators:

Artificial muscle actuators are for robots what biological muscles are for animals. There are wide variety of materials and configurations, which includes shape-memory alloys (SMAs), dielectric elastomers (DEAs), super-coiled polymers (SCPs), piezoelectric actuators (PZTs), and soft fluidic actuators (SFAs). Though they belong to a unifying class of artificial muscle actuators, these biomimetic actuators have historically been considered dissimilar and distinct technologies as they vary widely in terms of material, configuration, and scale; this induces significant challenges for robot designers to overcome. For one, when presented with the broad class of artificial muscle actuators, it is unclear to the typical robot designer how to select or even compare muscle actuators for use in their specific application.

We have the following parameters to compare the actuator that should be used according to designer's need:

- **Bandwidth:** The range of frequencies that the actuator can be excited continuously.
- **Efficiency:** The ratio of output work over input energy (the input energy can be in the form of electricity, heat, radiation, etc.).
- **Power Density:** The energy (work) density normalized to the actuation period.
- **Strain:** deformation required for the application
- **Stress:** force required for the task

### 1.3 Support Vector Machines

SVM is a machine learning algorithm used both for classification and regression. In this case, we are using it for multilabel classification. The objective of the SVM is to find a hyperplane in N-dimensional space that distinctly classifies datapoints. What this does to achieve this is that it finds a hyperplane with the maximum marginal distance from both the support vectors. The support vectors are the closest points to the hyperplane on either side of it.

# 2. Problem Statement

Given the task parameters for a certain task, we have to select the optimal soft actuator. This is governed by the parameters listed above.

### 2.1 Dataset

A list of actuators suitable for certain tasks with given parameters.

| Actuator Type | Bandwidth | Strain | Stress | Efficiency | Power Density |
|---|---|---|---|---|---|
| PZT | 10000.0 | 0.2 | 110.0 | 90.0 | 0.2 |
| PZT | 100.0 | NaN | NaN | 90.0 | NaN |
| DEA | 100.0 | 200.0 | 0.8 | 85.0 | 0.2 |
| IPMC | 10.0 | 40.0 | 0.3 | NaN | 0.02 |
| SMA | 3.0 | 5.0 | 200.0 | 1.3 | 50.0 |

There is a sparse data problem at hand and needs to be dealt with. We are planning to use Generative models for data generation and data normalization {log normalization} for better learning.

# 3. Methodology

The paper[1] implements 10-bivariate-SVMs for classification. It selects two features at a time and classifies the appropriate actuator. For datapoints with multiple features an ensemble of the models is used to arrive at the required actuator.

We plan to use Neural Networks for classification. Although NN perform poorly with sparse data, we are planning to counter this by data augmentation and generation. Currently we are using a NN of the following layer sizes: [5, 25, 9]. Adam optimizer is used in conjunction with sparse categorical cross entropy loss function.

# 4. Results

The best results for this classification task arise from the RBF kernel and with regularisation parameter lambda = 0.1. The highest accuracy came when we considered the Strain and efficiency columns (72%), the second highest with bandwidth and Power Density(67%) and third highest with the stress and strain feature columns(62%).

For Neural Networks an accuracy of 57% was achieved for an all-feature; 25 hidden nodes; single hidden layer architecture.

# 5. Conclusion

There is a lot of scope for improvement where we plan can augment the various SVMs and use an ensembled metric of confidence values to predict the appropriate class of actuator.

For neural Networks we can perform an exhaustive architecture search to see for best accuracy. We can also use GAN for data generation to counter sparse data problem.

# 6. References

[1]Taylor West et al, Data-driven Actuator Selection for Artificial Muscle- Powered Robots, 2021