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# Tactile Profile Classification using a Multimodal MEMs-based Sensing Module

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# Outline

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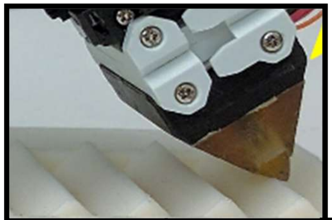
# Introduction

- Recognition of objects by touch is one of the first steps to enable robots to help humans in everyday activities.
- Many applications such as health and elder care, manufacturing, and high-risk environments involve tasks that require robots to handle objects that are out of their field of view or partially obstructed.
- Object recognition by touch can be divided in recognition through static or dynamic touch.
  - In static touch recognition, the tactile sensing apparatus establishes contact with an object and collects tactile data while the object is still related to the probe.
  - In the recognition through dynamic touch, the tactile apparatus gathers data while the sensors slide over the object's surface.

# Our approach

- This paper focuses on the issue of tactile profile recognition through a sliding motion performed by a robot finger comprises  3 motors equipped with a tactile probe.
- The tactile probe comprises a 9-DOF MEMs MARG (Magnetic, Angular Rate, and Gravity) system and deep MEMs pressure (barometer) sensor, both embedded in a compliant structure.
- This setup collects data over seven 3D printed profiles.
- The data collected is then subjected to a wavelet decomposition stage, principal component analysis and classification using a multilayer perceptron neural network.

# Our approach



Acceleration
Angular Velocity
Magnetic Field
Pressure

**Wavelet decomposition**

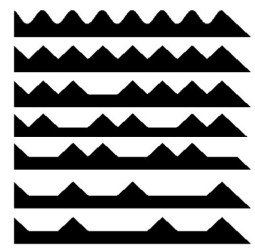
$5^{th}$ approx. level

**Principal Component Analysis**

90% of PCs

**Multilayer Perceptron Classification**

Shape Number



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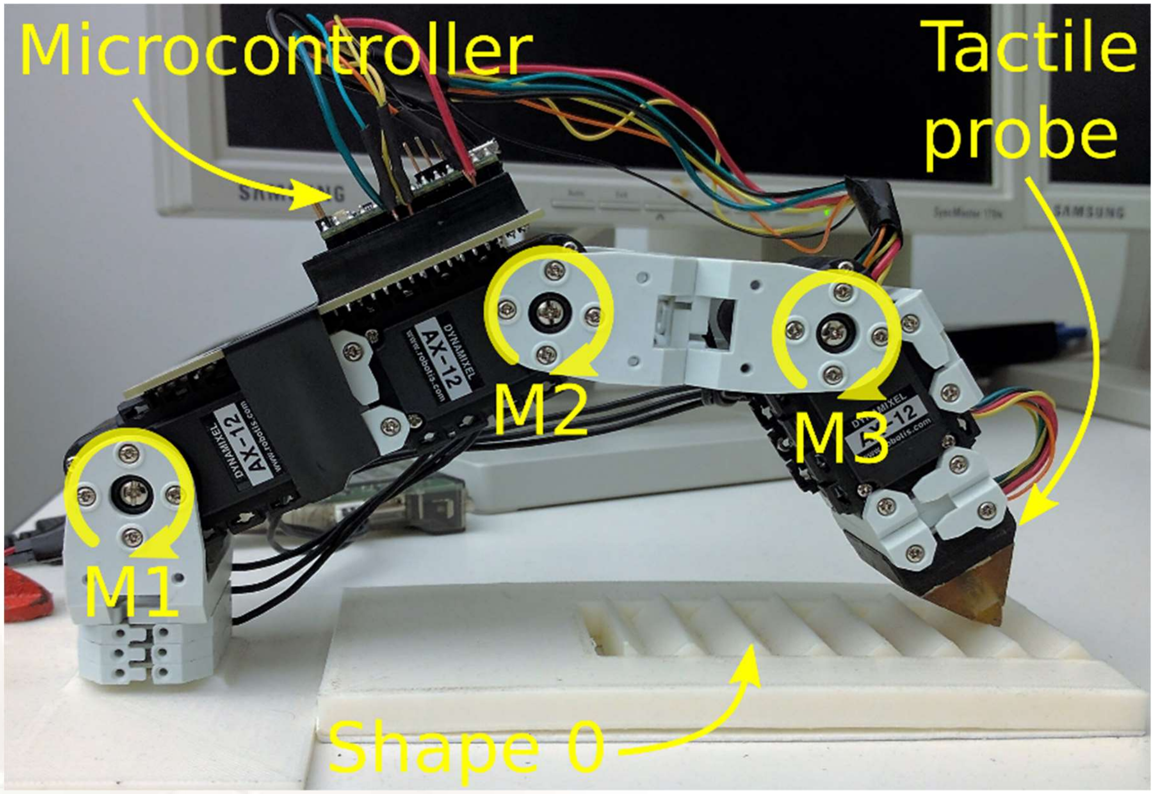
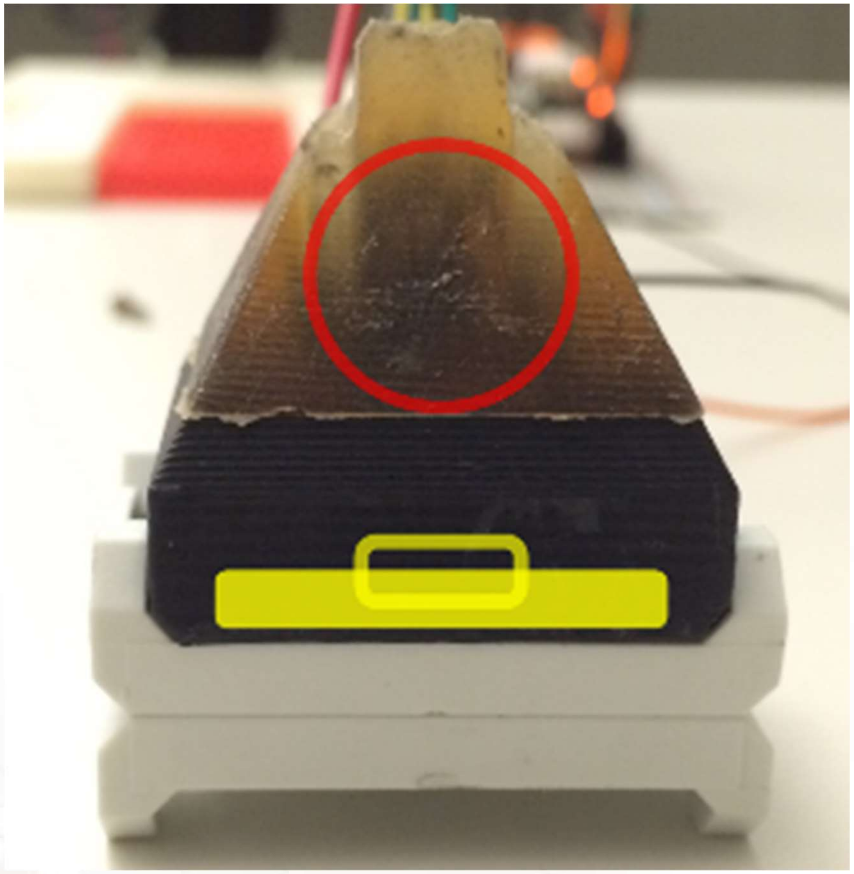
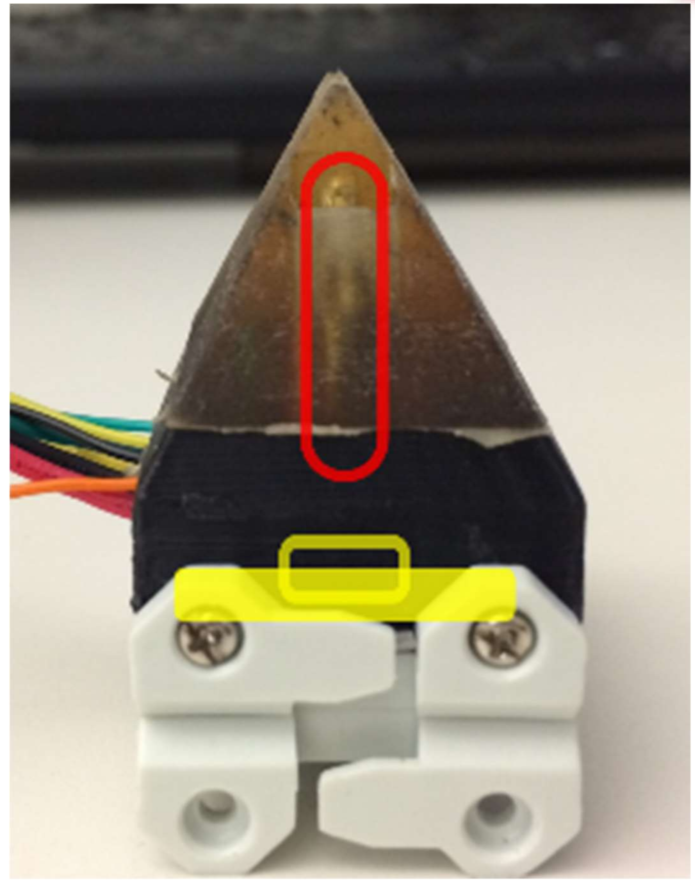
# Experimental setup



# Sensor placement





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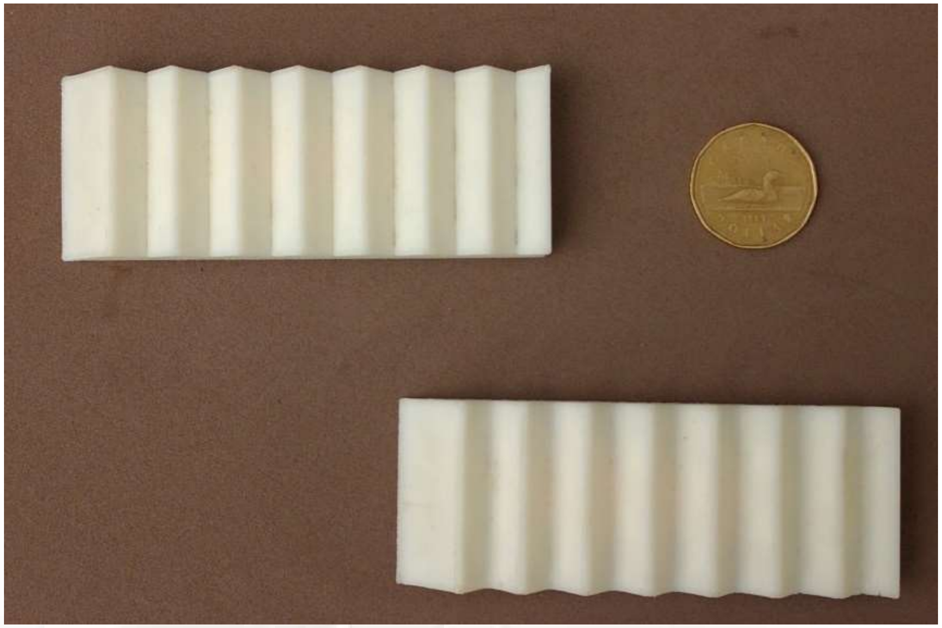
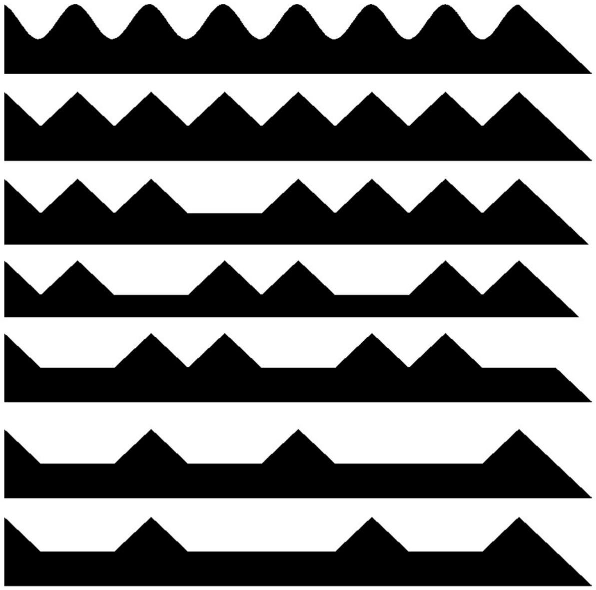
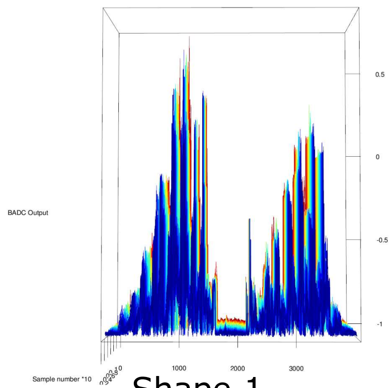
# Shapes used in the experiment

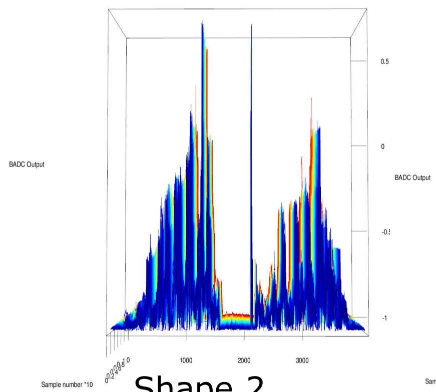




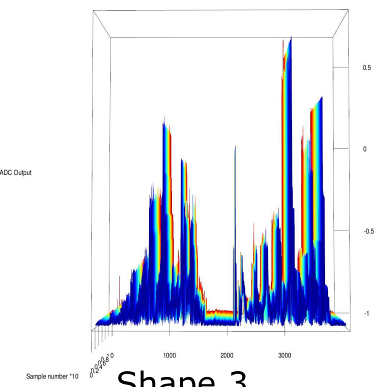
# Pressure output



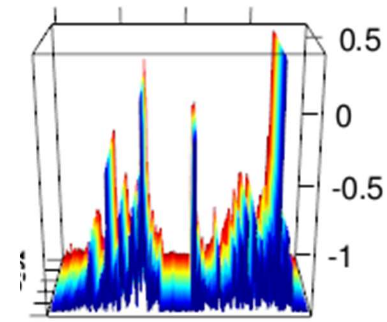
Shape 1



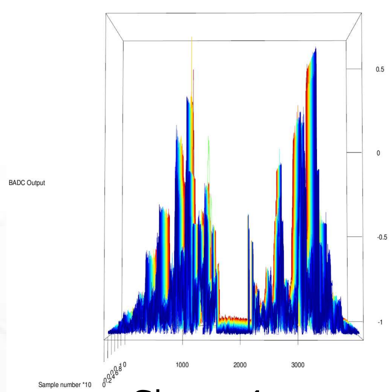
Shape 2



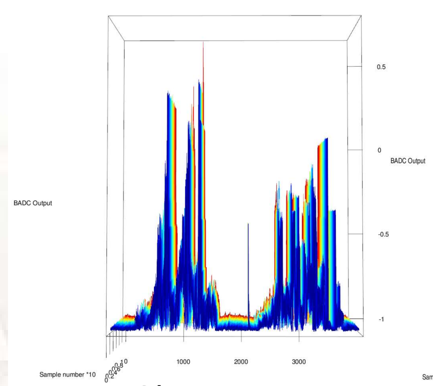
Shape 3



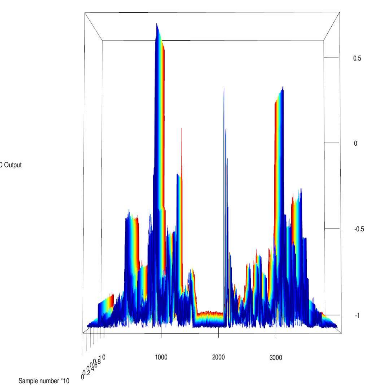

Shape 7



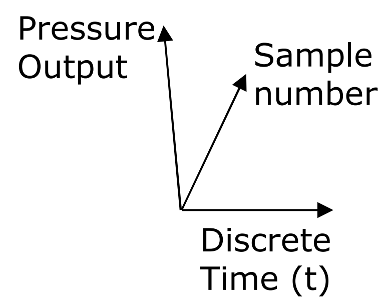
Shape 4



Shape 5



Shape 6



# Results

Classification results according to sensor type.

| Sensor | Accuracy (%) |
|---|---|
| Accelerometer X | 92 |
| Accelerometer Y | 92.6 |
| Accelerometer Z | 85.1 |
| Gyroscope X | 98.3 |
| Gyroscope Y | 93.3 |
| Gyroscope Z | 98.9 |
| Magnetometer X | 88 |
| Magnetometer Y | 86.9 |
| Magnetometer Z | 91.4 |
| Barometer | 98.9 |

# Results: Confusion tables

| Output Class \ Target Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| 1 | 25 14.3% | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 100% 0.0% |
| 2 | 0 0.0% | 25 14.3% | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 100% 0.0% |
| 3 | 0 0.0% | 0 0.0% | 25 14.3% | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 100% 0.0% |
| 4 | 0 0.0% | 0 0.0% | 0 0.0% | 25 14.3% | 2 1.1% | 0 0.0% | 0 0.0% | 92.6% 7.4% |
| 5 | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 23 13.1% | 0 0.0% | 0 0.0% | 100% 0.0% |
| 6 | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 25 14.3% | 0 0.0% | 100% 0.0% |
| 7 | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 25 14.3% | 100% 0.0% |
| | 100% 0.0% | 100% 0.0% | 100% 0.0% | 100% 0.0% | 92.0% 8.0% | 100% 0.0% | 100% 0.0% | 98.9% 1.1% |

| Output Class \ Target Class | 1 | 2 | 3 | 4 | 5 | 6 | 7 | |
|---|---|---|---|---|---|---|---|---|
| 1 | 23 13.1% | 8 4.6% | 6 3.4% | 3 1.7% | 0 0.0% | 0 0.0% | 0 0.0% | 57.5% 42.5% |
| 2 | 2 1.1% | 17 9.7% | 1 0.6% | 0 0.0% | 0 0.0% | 1 0.6% | 0 0.0% | 81.0% 19.0% |
| 3 | 0 0.0% | 0 0.0% | 18 10.3% | 0 0.0% | 0 0.0% | 1 0.6% | 0 0.0% | 94.7% 5.3% |
| 4 | 0 0.0% | 0 0.0% | 0 0.0% | 21 12.0% | 0 0.0% | 2 1.1% | 0 0.0% | 91.3% 8.7% |
| 5 | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 25 14.3% | 0 0.0% | 1 0.6% | 96.2% 3.8% |
| 6 | 0 0.0% | 0 0.0% | 0 0.0% | 1 0.6% | 0 0.0% | 21 12.0% | 0 0.0% | 95.5% 4.5% |
| 7 | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 0 0.0% | 24 13.7% | 100% 0.0% |
| | 92.0% 8.0% | 68.0% 32.0% | 72.0% 28.0% | 84.0% 16.0% | 100% 0.0% | 84.0% 16.0% | 96.0% 4.0% | 85.1% 14.9% |

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