Pattern Recognition Coursework 2025

Dr Ad Spiers (a.spiers@imperial.ac.uk)

Background

As humans, we use our sense of touch to help us classify and understand objects that we interact with. Touch is a useful alternative to vision when we can't see any object (due to poor lighting or occlusion) or an object property cannot be identified by sight (e.g. weight, softness). In this coursework we are going to investigate whether robots can also identify objects by touch. To do this we will use a new data set collected in the Manipulation and Touch Lab of Imperial College London.

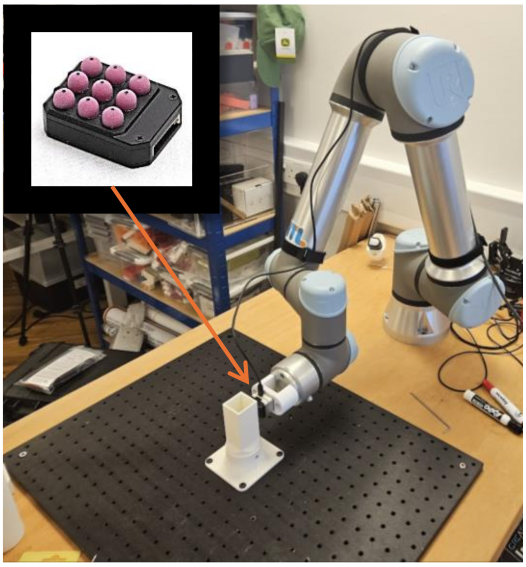

Figure 1: The experiment setup consists of a UR5e robot arm equipped with a Contactile sensor (inset). The test object is fixed in the workspace.

For the experiments, a UR5e robot was equipped with a 'Contactile' tactile sensor (Figure 1). The robot also includes a 6D force/torque sensor in the wrist. The Contactile sensor consists of 9 rubber papillae, each of which uses internal optical techniques to measure 3D vectors of force and displacement

The robot is tasked with making several precise and repeatable touching actions on nine different objects (Figure 2). Each experimental 'trial' refers to a series of touching actions with one object. The objects are changed between trials. During each trial the robot approaches the centre of the object from a given angle. Once the measured normal force (from the force/torque sensor) exceeds a given threshold, the movement stops.

The objects are controlled and consist of three cross sectional shapes (circular, square and hexagonal) and three different materials (3D printed PLA, 3D printed TPU and moulded rubber over a 3D printed PLA core.

As the robot carries out the experiment, various data is recorded from both the robot and the sensor. We are going to use pattern recognition techniques to determine if it is possible to identify the different objects based only on touch.

Note that in haptics and robotics, it takes a lot of time and expensive equipment to gather data, therefore the produced data sets are generally smaller than what is now considered typical for machine learning applications in other domains.

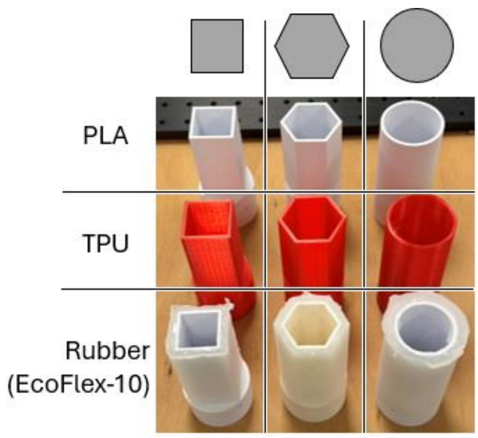

Figure 2: Nine objects are included in the dataset. These are composed of three geometric shapes and three materials. The rubber objects have a PLA core.

Thanks are due to Mr Jian Hou, a PhD student in the Manipulation and Touch Lab who wrote the code for the robot and sensors, fabricated the objects, ran the experiments and helped me format the dataset for this class.

Assessment

Assessment will be via a **5-page report** where you are expected to comment on observations you make from the various outcomes of the robot. Figures that are requested in questions are to be placed in the main body. Any other figures that you deem important can be placed in the appendix (which will not contribute to the page count).

You will be expected to submit your code in a self-contained fashion so that it can be run by me or a GTA if we need to check anything. The only thing we should have to do is switch the '/' and '\' for different operating systems. This means that .m and .mat files should be placed in the same folder, which can be zipped and submitted via blackboard. Comment your code – it is a <u>really</u> good habit! You can either submit one giant m-file or a separate m-file for each section. The m-file(s) should generate one figure per question, with subplots for the different parts.

Force Conventions

Force sensing on the robot and tactile sensors uses a slightly different axes convention. With the robot, the Z-axis points away from the wrist. With the tactile sensors it points towards the wrist. Note also the re-orientation of the X and Y axes.

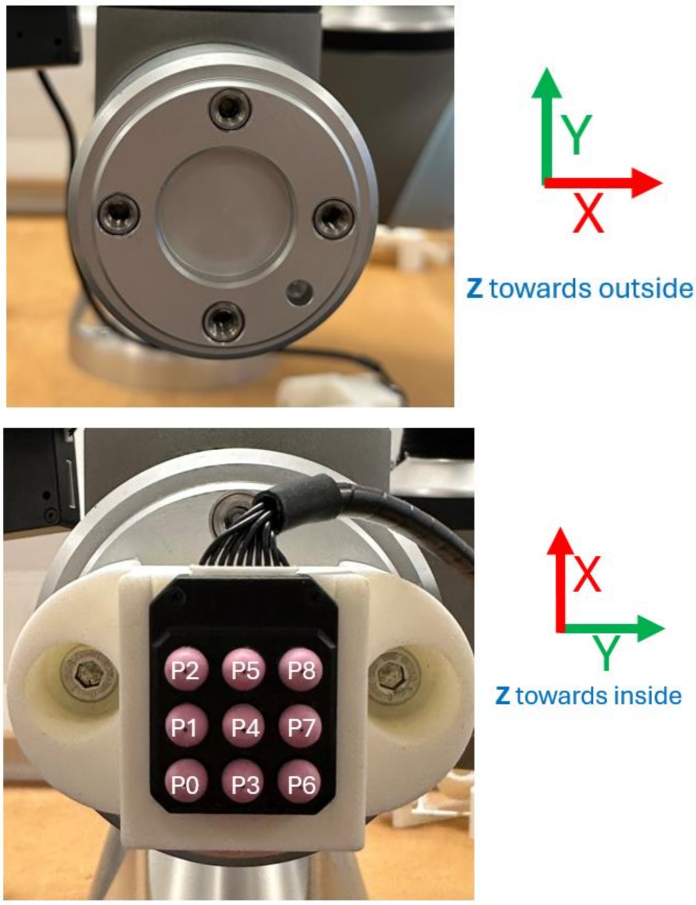

Figure 3: Force axis conventions

Instructions

Download the dataset from Blackboard. Use Matlab only for processing. You can use built-in Matlab functions, but nothing from Matlab File Exchange.

A. Data Preparation and Visualisation (10 marks)

1. For the cylinder and hexagon objects, view the **movement trajectory** of the robot's end effector. Plot these and include them in your report. What is different about these trajectories?

2. The recorded trial data consists of long time series involving multiple contacts for each object. **Segment** the data into individual object contacts.
   a. Using the force/torque sensor readings, determine the instances of maximum normal contact force. Display a figure showing these peaks and their time index.
   b. Save the peaks and indices for each object
   c. Using the peaks and indices, extract the tactile sensor data (force and displacement) and force/torque sensor data for each maximum force contact. Save this data.

3. The Contactile tactile sensor is composed of 9 individual domed sensors called papillae (shown in Figure 1 and Figure 3). Right now, we're just going to look at the data from the middle papillae (P4).
   a. For the 3 cylinders (normal, TPU and rubber), create a 3D scatter plot of the **force data** from the **middle papillae** (so, the X axis is the force in the X direction and so on). Use a different colour for each object. Keep using the same colours for the rest of your report.
   b. Choose one of the **corner papillae** and re-plot the data. What differences do you observe and why do you think those differences are present?

B. Principal Component Analysis (25 marks)

1. Apply **PCA** to the **force data** of the **middle sensor** for all three cylindrical objects.
   a. Replot the standardised data with the principal components displayed.
   b. Reduce the data to 2-dimensions and replot.
   c. Show how the data is distributed across all principal components by plotting as separate **1D number lines**.
   d. Comment on your findings.

2. So far, we've only been looking at 3-dimensional data (the force vector from one papillae). However, we've got 9 papillae at our disposal. Consider the force data from **all nine papillae** when answering the following.
   a. Create a **Scree** plot, showing the variance of all principal components. What does the scree plot tell us?
   b. Show how the data is distributed across the first three principal components by plotting as separate **1D number lines**.
   c. Reduce the data to 2 dimensions and replot
   d. Given the results so far, comment on the benefit/drawbacks and effects of including all the papillae in the analysis, instead of just P4.

C. Linear Discriminant Analysis (20 marks)

1. We want to see if we can discriminate the same shape object made of two different materials via the central papillae **displacement** using Linear Discriminate Analysis (**LDA**).
    a. Load the data for the 'Oblong TPU' and 'Oblong Rubber' objects
    b. Visualise the tactile displacement with a 3D scatter plot. What can you observe?
    c. Apply **LDA** to all 2D combinations of D_X, D_Y and D_Z and visualise your outputs
    d. Now apply LDA to the 3D displacement data
        i. Reduce to 2 dimensions and re-plot (with **LD and discrimination lines**)
        ii. Show the 3D plot (with **discrimination plane**)
    e. Comment on the different outcomes. Consider the physical properties of the objects in your answer and how these may have affected the sensor readings

Part 2

D. Clustering & Classification (30 marks)

1. Choose either the hexagon or oblong objects. Use the data only from the central papillae.
    a. For the 3 different materials create a scatter plot, with each material represented by different colour markers.
    b. Now apply a **clustering algorithm** of your choice (that we covered in class) to the same data. Visualise the outcome. Comment on whether the clusters correspond to real-life outcomes. Propose reasons for the outcome.
    c. Now change the **distance metric**, repeat the clustering and comment on the change in outcome.

2. Now apply **bagging** (bootstrap aggregation) to the displacement data from **all nine** papillae that was **previously processed with PCA** (in question B.2.c).
    a. Specify the number of bags / trees you used. Why did you choose this number?
    b. Visualise two of your generated decision trees
    c. Run the trained model with the test data. Display a **confusion matrix** (where the object type is the class) and comment on the overall accuracy.
    d. Discuss the following: How can misclassifications in your results be explained given the object properties? Do you think the PCA step was helpful?

E. Conclusion (15 marks)

1. Summarise your work.
    a. How have the PR techniques helped us analyse the data?
    b. Would you say it is possible to distinguish objects by touch?
    c. Our analysis currently treats all contacts as the same. How could you change this and what would be the benefits/ drawbacks of your proposal?
    d. Our analysis is currently based on a single time step, but we have much more data in our original time series. How could you change this and what would be the benefits/ drawbacks of your proposal?

Appendix - Variable names

end_effector_poses - the position [1x3] and orientation [1x3] of the UR5e's end effector

ft_values – values of the force/torque sensor. Forces [1x3 – x,y,z] and torques [1x3 – roll, pitch, yaw]

sensor_matricies_force – there are 9 papillae, each with an [1x3] force vector. These are arranged in the sequence given in Fig 3 to give 27 (9x3) variables per row.

sensor_matricies_displacement – same as force, but now each papillae has a [1x3] displacement vector.

angle & **selected** – ignore these