Pattern Recognition Coursework 2021

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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). In this coursework we are going to investigate whether robots can also identify objects by touch. To do this we will use a large and complex data set collected with some very expensive hardware by at the University of Pennsylvania's GRASP lab (USA).

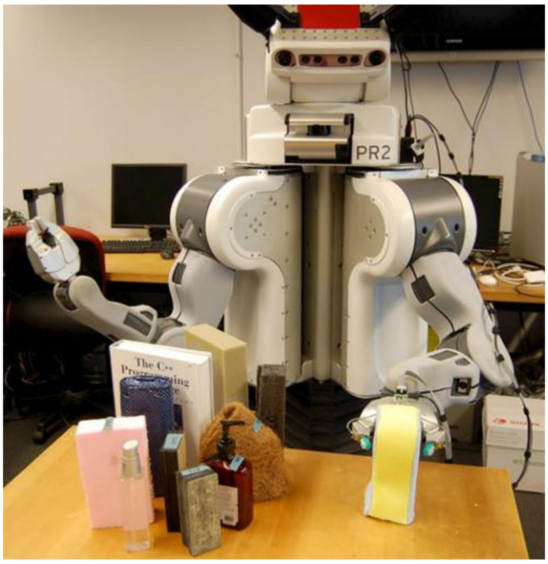

Figure 1: The *PR2* robot at UPenn collecting haptic object data with two *BioTac* tactile sensor fingertips.

For the experiments, a **PR2** robot ($400k) was equipped with two **BioTac** tactile sensors ($15k each) on its 2 finger gripper. The robot then manipulated several different objects while various the tactile data (pressure, temperature, vibration and 19 electrode measurements) were collected. You can watch a video of the data collection here: https://youtu.be/_pmqs85HRjs

We are going to use pattern recognition techniques to answer the following two questions:

A. Can the tactile sensors be used by the robot to identify objects by grasping them?
B. Could cheaper finger hardware also identify different objects if it had less sensor types? If so, which sensors should we remove / keep and what would the performance be like?

Note that in haptics and robotics, it often takes a lot of time and expensive equipment to gather data, therefore the produced data set is generally smaller than what is now considered typical for machine learning applications (particularly deep learning).

Thanks are due to Ben Richardson, a PhD student at the Max Planck Institute for Intelligent Systems (Germany) who helped me to prepare this dataset for use in this class.

Assessment

Assessment will be via a 3 page report where you are expected to comment on how different algorithms perform with regard to the sensor type, objects and task. These comments are specified in the instructions. Figures can be placed in the Appendix, which will not count to the page limit. This coursework is to be completed in **Matlab**. You may use Matlab's built in functions.

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.

Instructions

Download the dataset from Blackboard and open it in Matlab.

Section A: Data Preparation - **[10 marks]**

1. Use the plot command to view the time series sensor data for the variables *Pressure*, *Vibration* and *Temperature (PVT)* and the *Electrodes*. Do this for several objects and trials and then choose a single time step that looks like it will allow differentiation between the data for different objects. Explain why you chose that value. Include an example of your data visualisation for one or two object trials in your report.

2. For one finger (F0 or F1), sample the *Pressure*, *Vibration*, *Temperature* time series data into scaler values measured at the time instance (of your selected time step) for each object / trial. Save the data structures together as a .mat file called F0_PVT.mat or F1_PVT.mat. Repeat for the *Electrodes* data, saving that as another .mat file. Note that all subsequent actions in this coursework will be on the data sets you just created (and therefore only on one of the robot's fingers).

3. Create a 3D scatter plot of the complete contents of the PVT mat file, with the axis as Pressure, Vibration and Temperature, with different colours used for different objects. Use the same colours for the objects throughout this work.

Section B: Principal Component Analysis **– [25 marks]**

1. Using **PCA** (Principal Component Analysis) determine the principal components of the **PVT** data.
   a. Report **covariance matrix, eigenvalues, and eigenvectors** for the data.
   b. Replot the Standardised data with the Principal components displayed.
   c. Reduce the data to 2-dimensions and replot.
   d. Show how the data is distributed across all principal components by plotting as separate 1D number lines.
   e. Comment on your findings.

2. There are 19 electrodes per sensor, so relationship between the electrodes for different objects cannot be easily visualised as in the last questions.
   a. Use **PCA** to determine the principal components of the **electrode** data. Report on the variances of each principal components using a **Scree plot**.
   b. Visualize the electrode data using the three principal components with largest variance.
   c. Comment on your findings.

Section C: Linear Discriminant Analysis (LDA) - **[20 marks]**

1. We want to see if we can discriminate two deformable and porous objects by touch: the black foam and the car sponge.
    a. Use **LDA** to split the training data in terms of Pressure vs. Vibration, Pressure vs. Temperature and Temperature vs. Vibration. Plot the results, including a line showing the generated LDA function.
    b. Now apply **LDA** to the three-dimensional PVT data.
    c. Comment on the different outcomes. Consider the physical properties of the objects in your answer and how these may have affected the sensor readings.
    d. Repeat the LDA analysis with **your own choice** of two objects. Explain why you have selected those objects for analysis. In other words – what were you trying to test and what did you determine?

Section D: Clustering & Classification **- [30 marks]**

1. Apply your choice of a **clustering algorithm** (that we covered in class) to the PVT data
    a. Visualise the output.
    b. Comment on the outcome. Do the clusters correspond to real-life object similarities?
    c. Change the **distance metric,** repeat the clustering and comment on the change in the outcome.

2. Now apply **bagging** (bootstrap aggregation for an ensemble of decision trees) to the **electrode data that was processed with PCA** in section B.2.b. Use a 60 / 40 split for Training / Test data.
    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?

Section E: Conclusion **– [15 marks]**

1. Summarise your work.
    a. How have the pattern recognition techniques helped us analyse the data?
    b. Would you say it is possible to distinguish the objects only using touch?
    c. If you wanted to repeat the experiment with a cheaper tactile sensor (one with fewer sensing modalities and/or electrode channels than the BioTac), what object properties do you think would be most important for that sensor to measure? Justify your answer based on your findings.
    d. Our analysis is based on a single time step access all the available data sensor data. Discuss an alternative method we could use to prepare the data for pattern recognition. What are the pros and cons of this other approach?