Report for CVPR Coursework

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1. Task A: Data Preparation

Time step selection The first task was to view the time series sensor data for pressure, vibration and temperature (PVT data). By inspecting the feature of PVT data, a significant transient stage was discovered in the curves that visualizing PVT data. In transient stage of contact, according to D Erickson [2], the system is of high randomness, noise, and non-linearity. Therefore, to process the data with only one time step, the data at the position of 800, at which point the system can be considered as of a steady state. There are two curves being presented in the figure below.

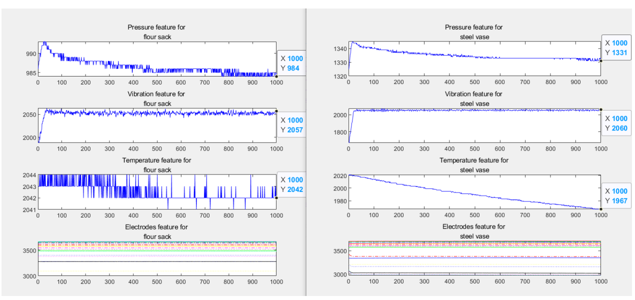

Figure 1: Visualisation of pressure, vibration, temperature, and electrodes of flour sack and steel vase

3D scatter plot The 3D scatter plot is generated by using Pressure, Vibration, and Temperature as axis. The 3D scatter plot would be presented in figure 2. Different colours were used for different objects, which would be the same in the later text.

2. Task B: Principle Component Analysis

Part 1 The data obtained in the last section is first standardized to remove bias from different variable ranges. The covariance matrix, eigenvalues, and eigenvectors are presented below:

$$S = \begin{bmatrix} 1.0000 & 0.0405 & -0.6221 \\ 0.0405 & 1.0000 & 0.0261 \\ -0.6221 & 0.0261 & 1.0000 \end{bmatrix} \tag{1}$$

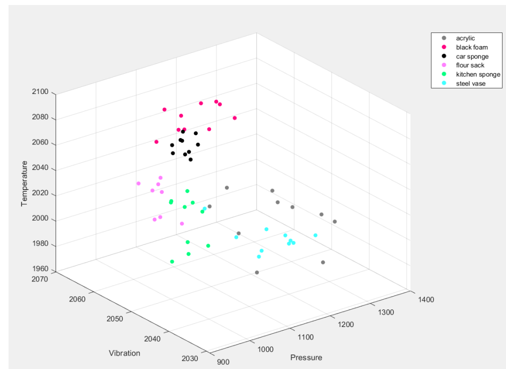

Figure 2: 3D scatter plot of the data sampled at 800 time step

$$eigenvalues = \begin{bmatrix} 0.3744 & 0 & 0 \\ 0 & 1.0034 & 0 \\ 0 & 0 & 1.6222 \end{bmatrix} \tag{2}$$

$$eigenvectors = \begin{bmatrix} -0.7055 & -0.0414 & -0.7075 \\ 0.0750 & -0.9970 & -0.0165 \\ -0.7047 & -0.0647 & 0.7066 \end{bmatrix} \tag{3}$$

Standardization was conducted before procession. In the figure 3 (In the appendix), the standardised data are visualised with Principle components. Compared with figure 2, the standardized data shown in the figure 3 preserved the same distribution features.

The data are then reduced to 2-dimensions and visualised in the figure 4 in appendix(All the figures below in this report are presented in appendix). In the figure 4, the grouping features are obvious and the most of the features of different objects were preserved.

From the above steps, the principle components are determined and the data are projected to a 2D plane with the first and second eigenvectors as the new axis. By projecting all the data on the feature vectors, in figure 5, it can be observed that the variance of the data are decreased. Therefore, some pattern of the data can be found, making it possible for further discriminating and clustering the data.

Part 2 For electrode data, principle components analysis was firstly applied to the data of 19 dimensions. As a result, the dimensionality of the electrodes data was reduced to 3. The variances feature of each principle components are shown with scree plot in figure 6, from which it can be discovered that there are two dimensions in the electrode data contributed to the majority portion of the variance. In other word, two dimensions in the data set may be significant the most for distinguishing objects.

In figure 7 (presented in appendix), the three principle components with largest variance are selected as three axis to visualise the data. By observing the scatter plot, it can be discovered that though the data points were separated, it is difficult to classify the data.

3. Task C: Linear Discriminant Analysis

Data splitting The training data points were separated in terms of Pressure and Vibration(figure 8), Pressure and Temperature(figure 9), and Temperature and Vibration(figure 10). The resulted figures are being presented in appendix.

Part 1 Then in figure 11, LDA was applied for splitting of three-dimensional PVT data.

From the results of the two approaches, it is quite clear that the splitting of data is not successful when only two dimensions of data are used. In real-life, it is of high similarity between black foam and car sponge, which is manufactured of the same material and similar structure. Therefore, distinguishing these two objects is challenging with contacting sensory. From numerical point of view, the similarity of physical properties between the two objects are proved by comparing the means for sponge and foam in all the three dimensions.

Flour sack and steel vase are selected to repeat the analysis because their physical properties are significantly different. The results are shown in figure 12-14. The results have proved that by using LDA different class of data are better separated compared with that of black foam and car sponge.

Then LDA is applied for splitting flour sack and steel vase with PVT data points. The splitting result would be presented in figure 15.

4. Task D: Clustering and Classification

Part 1 A clustering algorithm is applied to the data and the grouping result is shown in figure 16.

The clustering results correspond to their similarities. For sponges and foam, their physical properties are similar since they are both very soft, hence the data of the same object are mostly grouped together. Similarly, acrylic and steel vase are both stiff and is not easy to be distinguished and grouped. While for acrylic and sponges or foam and steel vase, the soft and tough objects can be easily distinguished, but detailed clustering is not that accurate. There is little difference when changing the distance metric, as is shown in figure 17 in appendix.

Part 2 The number of bags used is set to be 120 after multiple testing because it gives the best results.

The visualised decision trees are shown in figure 18 and 19 in appendix.

The confusion matrix is displayed in figure 20. A high number for bags (in the code, training time) would cause over fitting, which would reduce the accuracy of classification. Therefore, the best way to increase the performance of current program is to design an early stopping mechanism.

Misclassifications can be explained by the similarity of objects and the distribution of data points. PCA step is highly helpful for analyzing electrode data. There are 19 dimensions in the original data structure. Therefore, dimension reduction of high importance for reducing the dimensionality into 3 dimensional data.

5. Task E Conculsion

Summarise By applying PCA methods, the data are projected in the direction where its variance is maximized and the principle components are found. Then LDA technique is used given different classes of data for separating and clustering. The results of hierarchical clustering is also visualised using dendrogram to show the distance between points and how they are grouped intuitively. Finally, bagging is applied to decision trees for classification.

Distinguish It depends on what objects are to be distinguished. As in section D, the classification of different objects and there are successful cases. If the physical properties of the objects are quite different from each other, for instance a soft one and a tough one, then it is possible to separate them only by touching.

However, in this project, only the data at one time step was applied for analysis, which making it mathematically impossible to analyze the first order derivative feature. By sampling more data points, objects can be distinguished by using touching [2],[1].

Critical property The most important property to be measured, based on the eigenvalue of PVT data set is the temperature (it is the most significant principle component). However, referring to the figure 1, the temperature is not converged to a certain value. Therefore, the vibration data can be considered as of the most significant, which means that the pressure sensory is of the highest importance when implementing tactile sensors.

Alternative method The advantage of using the sensor data at one time step is that the processing speed can be high for the data amount is relatively low. However, the disadvantage is that the features of higher mathematical order can not be evaluated.

Alternatively, more data can be used for processing by sampling at a certain frequency, which would enable conducting analysis of high order features. However, the complexity would be increased and processing speed would be decreased due to so called the curse of dimensionality.

References

[1] F. M. P. Behbahani, G. Singla-Buxarrais, and A. A. Faisal. Haptic slam: an ideal observer model for bayesian inference of object shape and hand pose from contact dynamics.

[2] D. Erickson, M. Weber, and I. Sharf. Contact stiffness and damping estimation for robotic systems.

6. Appendix

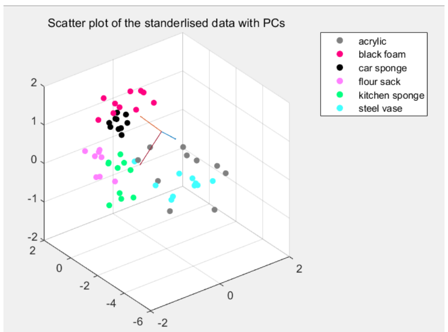

Figure 3: Scatter plot of the standardized data and principle components

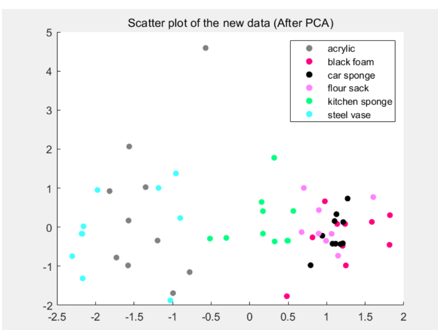

Figure 4: Scatter plot of the data after reducing the dimension of it into 2D

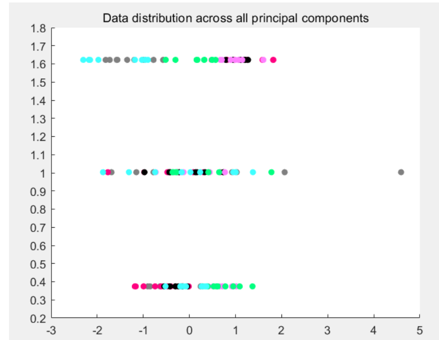

Figure 5: 1D projection on different principle components

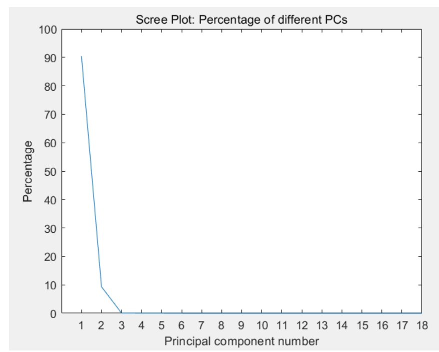

Figure 6: The scree plot of the 19D electrode data

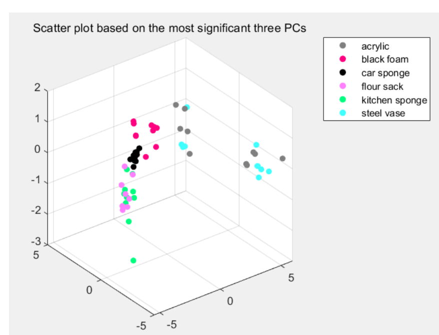

Figure 7: 3D scatter plot of electrode data after reducing the dimensionality to 3

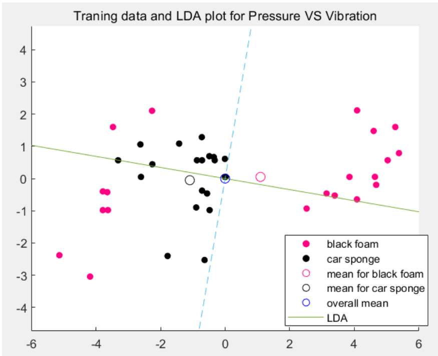

Figure 8: Scatter plot of data points (black foam and car sponge) and LDA with dimension of Pressure vs Vibration. The dash line is the discrimination line

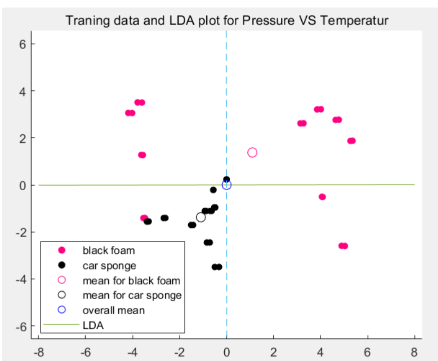

Figure 9: Scatter plot of data points (black foam and car sponge) and LDA with dimension of Pressure vs Temperature. The dash line is the discrimination line

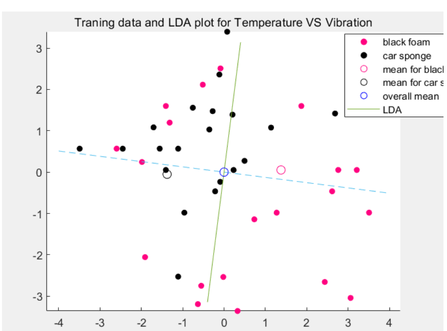

Figure 10: Scatter plot of data points (black foam and car sponge) and LDA with dimension of Temperature vs Vibration. The dash line is the discrimination line

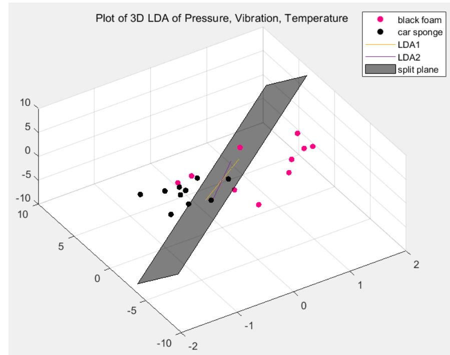

Figure 11: The plot for splitting PVT data points of black foam and car sponge

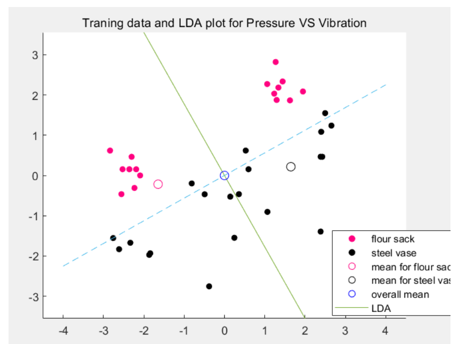

Figure 12: Scatter plot of data points (flour sack and steel vase) and LDA with dimension of Pressure vs Vibration. The dash line is the discrimination line

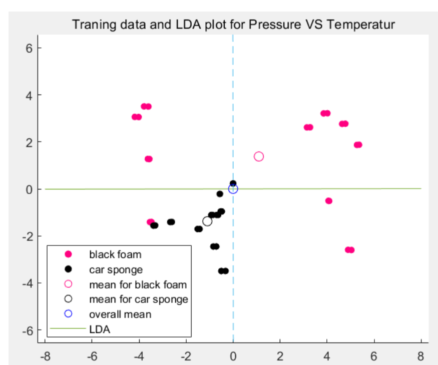

Figure 13: Scatter plot of data points (flour sack and steel vase) and LDA with dimension of Pressure vs Temperature. The dash line is the discrimination line

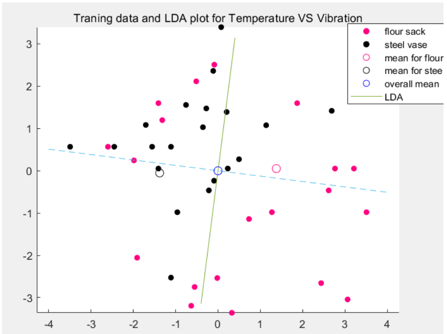

Figure 14: Scatter plot of data points (flour sack and steel vase) and LDA with dimension of Temperature vs Vibration. The dash line is the discrimination line

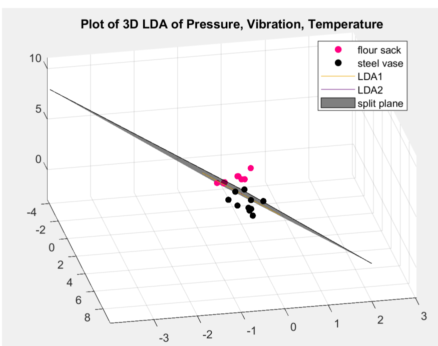

Figure 15: The plot for splitting PVT data points of black foam and car sponge

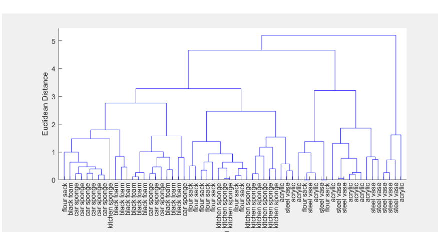

Figure 16: The clustering result using Hierarchy algorithm with distance metric 'euclidean' distance

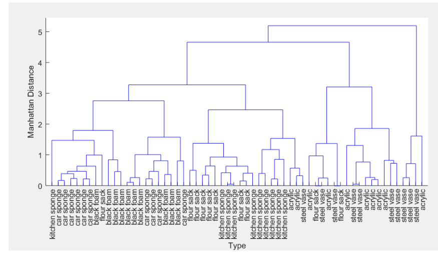

Figure 17: The clustering result using Hierarchy algorithm with distance metric 'cityblock' (or say 'Manhattan') distance

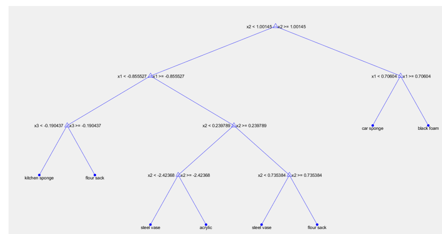

Figure 18: The initial tree generated after the first epoch of training

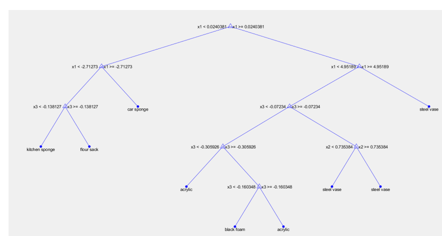

Figure 19: The final tree generated for further classification

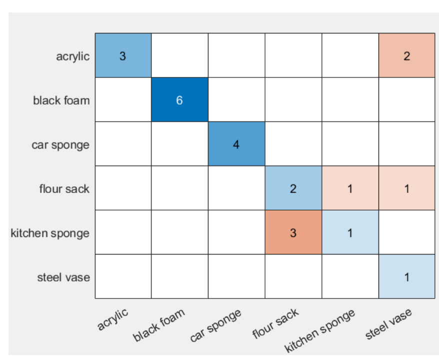

Figure 20: Confusion matrix of final classification

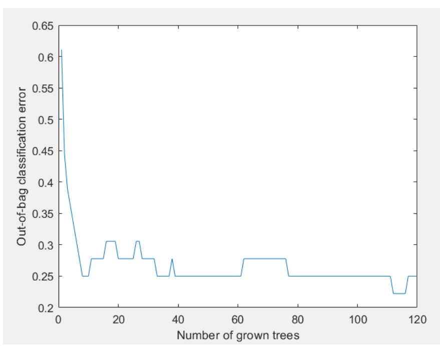

Figure 21: Out-of-bag classification error with respect to different epochs