Week 6 Practical

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CAB420: Machine Learning

This weeks practical will focus on Principal Component Analysis and Linear Discriminate Analysis.

Problem 1. EigenFaces. Consider the EigenFaces lecture example (*CAB420_Dimension_Reduction_Example_5_Eigenfaces.ipynb*). Using this example, and the PCA space that is learned on the YaleB Face Dataset, investigate the face recognition performance of two additional datasets: *Yale_32x32.mat* and *ORL_32x32.mat*. For each of these you should:

1. Use the PCA space learned on the YaleB data (i.e. don't learn a different PCA space on the new data);
2. Ensure that the new data is resized to the same size as the YaleB data prior to use;
3. Train a simple KNN classifier (or another classifier of your choosing), using roughly 66% of the data as training, and the rest as testing;
4. Evaluate the accuracy of the predictions with different numbers of components retained;
5. Visually inspect reconstructions with different numbers of components retained, and comment on the quality of the reconstructions for the two databases.

Problem 2. FisherFaces. Linear Discriminant Analysis is designed to find a re-projection of the data such that it maximises the distance between the classes, while ensuring that samples of the same class are tightly grouped. As such, it has been widely applied to biometrics. One such method is *FisherFaces*, which applies PCA and then LDA to help group faces of the same subject. In brief, *FisherFaces* operates as follows:

1. Construct an image matrix, where each row is a vectorised version of an image (i.e. as was done for EigenFaces)
2. Project this matrix into an $N - C$ (N is the number of samples, C is the number of unique classes) using PCA.
3. Apply LDA to the subspace that results from the PCA transform, i.e.:
   (a) Compute the between class scatter matrix in the projected space;

(b) Compute the within class scatter matrix in the project space;

(c) Compute the eigenvalues and eigenvectors of the ratio of the scatter matrices.

4. Learn a classifier (i.e. k-nearest neighbours) in the final LDA space.

New samples can now be mapped to the *FisherFace* space by applying the PDA projection followed by the LDA projection.

Using this classifier:

1. Compare the performance of LDA and PCA using the test set of the YaleB dataset.

2. Compare the performance of LDA and PCA using the two additional datasets the: *Yale_32x32.mat* and *ORL_32x32.mat*. As per Question 1, do not re-train the PCA or LDA subspace using this data.

3. Compare the performance of *EigenFaces* as the number of retained PCA components changes, to *FisherFaces* when equivalent changes are made to the number of retained components in the LDA space (note, do not reduce the number of components in the initial PCA projection for *FisherFaces*).

More information on FisherFaces can be found in the original paper [1], or online in posts such as this one: `https://www.bytefish.de/blog/fisherfaces/`.

References

[1] K. Etemad and R. Chellappa, "Discriminant analysis for recognition of human face images," in *Audio- and Video-based Biometric Person Authentication*, J. Bigün, G. Chollet, and G. Borgefors, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 1997, pp. 125–142.