ECE 7868 Project 2 Report

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Abstract

In this project, I applied the Principle Component Analysis (PCA), Independent Component Analysis (ICA) and Linear Discriminant Analysis (LDA) into image compression. I call it image compression since I used very few components of PCA, ICA and LDA to represent the image, which decreases the dimension. Then I got the multivariate normal distributions based on their means and covariances in the subspace, and I drew some samples from these multivariate normal distributions.

1 Problem 1: Image Compression

The main idea of image compression is using fewer vectors to linearly represent the images. Thus I considered PCA, ICA and LDA and used the components of these methods to create the subspaces V_k, which has basics $\{v_{k1}, \cdots, v_{ks}\}$. I projected the original images onto these subspaces to compress them.

For simplicity, I transformed the colorful images to gray images, and in ICA and LDA, I used the first 4 faces because the algorithms are slow when the number of groups increases.

1.1 PCA

In this experiments, I used the AR face dataset. For each person, I used his/her images to create a PCA subspace $V_k = (v_{k1}, \cdots, v_{ks})$. Here, I chose $s = 10$ (i.e., I choose the first 10 principle components) so I can compress the image onto the 10 dimension space. I projected the images using the formula $t^T V_k V_k^T$, where t is an image vector of the k person. Some sample results are showed in Figure 1.

1.2 ICA

Similarly, I got the components of ICA using the *Fast ICA* algorithm for each person. However, all components in ICA are equally important, so I just choose the first 20 components derived from the algorithm. Another problem is that these components are not orthonormal, which is inconvenient to do the projection. Therefore, I used the *Gram-Smith Orthogonalization* to get the orthonormal basics $V_k = (v_{k1}, \cdots, v_{ks}),\ s = 20$ for each person. The results are also showed in Figure 1.

1.3 LDA

To calculate the LDA components, we need to include all classes together, which is different from PCA and ICA. Because the number of samples is 104 (4 faces), but the number of features is 19800, it is infeasible to implement the LDA directly. Thus I used the PCA to reduced the dimension of features to 40 and then implemented the LDA on the PCA subspace. I used the *Gram-Smith Orthogonalization* to get $s = 3$ basics of the LDA subspace. Finally, I projected the original images onto the PCA space then projected it onto the LDA subspace, so I can get the projection on the LDA space approximately. The results are showed in Figure 1.

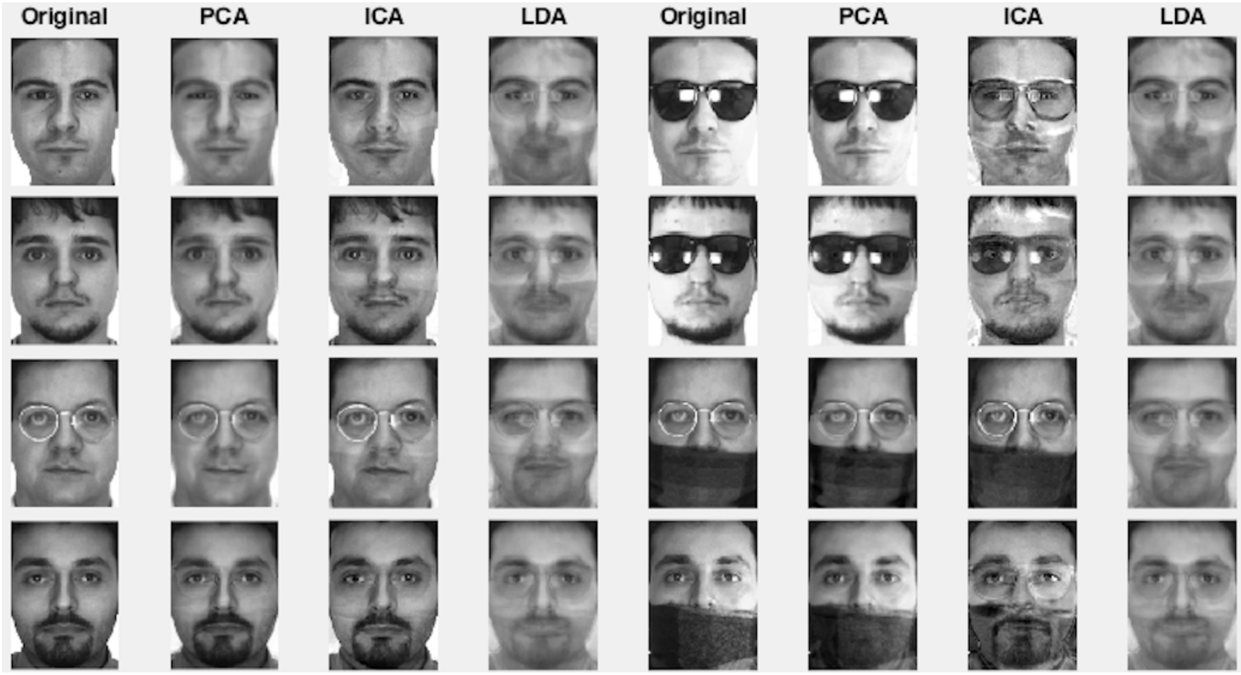

Figure 1: The image compression using the PCA, ICA and LDA. In the same row, the images are showing the same person.

2 Problem 2: Random Sample from Subspace

By computing the mean and covariance matrix of the images' projection in the PCA, ICA and LDA subspace, I can defines the normal distribution of the images in these subspaces. I drew samples from this normal distribution to generate the new sample images. The results are showed in Figure 2 .

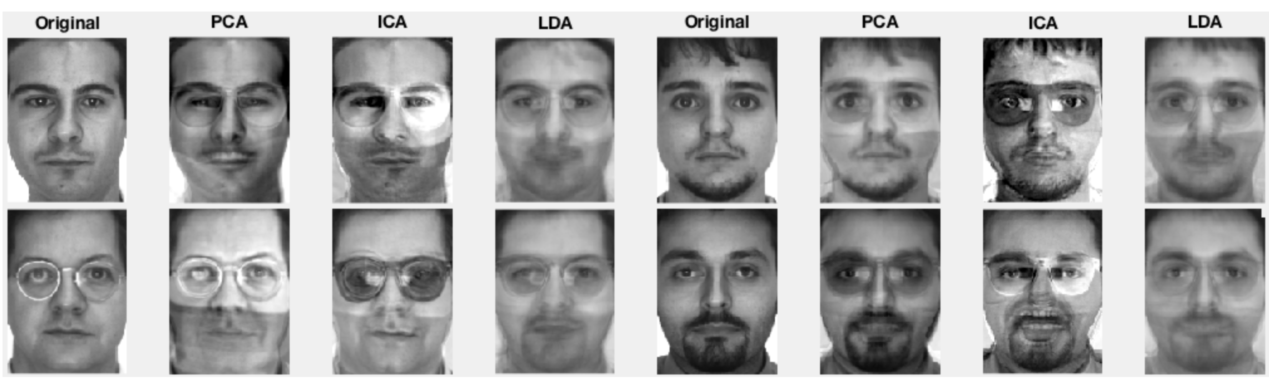

Figure 2: The random samples drew from the normal distribution in PCA, ICA and LDA subspace.

3 Discussion

In these experiments, I can see that the PCA has better performance in image compression, and ICA is good in representing some specific features (likes glasses), but they have large within group variance in their subspace. LDA has small within group variance in subspace but has large between group variance, so for the same person, the recovering is nearly the same.