ECE 7868 Project 3 Report

Lingfei Zhao

Abstract

In this project, I classify the images by applying the Gaussian Mixture Model (GMM) on each object in their original space or PCA, ICA and LDA subspace. I first project the images onto the PCA, ICA and LDA subspaces, then estimated their underlying mixture Gaussian distribution by EM algorithm. Finally, by Maximum Likelihood Estimation, I can categorize the new image into a category which is the most likely. Also, I generate samples using the estimated mixture model in their original spaces, PCA, ICA and LDA subspaces.

1 Gaussian Mixture Models

1.1 Estimation

I projected the training data to their original, PCA, ICA, LDA spaces. Given a classe C_k, I am interested in its distribution in each space, $p(x|C_k)$. I model the class conditional probability $p(x|C_k)$ using the Gaussian mixture model: $p(x|C_k) = \sum_{j=1}^{M} p_k(x|j)P_k(j)$, where I assume $p_k(x|j)$ is a Gaussian distribution with mean μ_{kj} and covariance matrix Σ_{kj}. To reduce the number of parameters and avoid getting ill-conditioned covariance, diagonal covariance matrices are used. And since I perform PCA in advance, I can assume that the of correlation of different features are small. (There is a reference in ReadMe.)

The number of mixtures $M = 4$ is predefined because I find when $M = 4$, the algorithms converge and get good result. If M is too small or too large, the result may be underfitting or overfitting and the results are influenced.

I implement the EM algorithm with random intinal points to estimate the GMM. Sometimes the algorithm does not converge in a given step.

1.2 Classification

Given an image x, I am interested in the probability that x belongs to class C_k, $p(C_k|x)$. I assume equal priors for all classes, then using the Bayes rule and the Maximum Likelihood Estimation, I can determined the class for x is $C^* = \arg\max_{C_k} p(C_k|x) = \arg\max_{C_k} p(x|C_k)$.

Because I use the PCA, ICA and LDA subspace, I need to project the testing data onto the subspace at first, then I can calculate the likelihood.

1.3 Experiments

I used ETH-80, CIFAR-10, AR face dataset in this experiment. I randomly choose 80% data as training data and 20% data as testing data. In order to reduce the dimension of the features and let the computation become feasible, I use black&white images in ETH-80 and AR face. I also use PCA at first and select many components to let them contains almost all information of the original space. Then I can calculat the GMM on original space and get the ICA conponents and LDA components based on it.

In CIFAR-10 dataset, the number of samples is large, and the *Fast ICA* algorithm runs slowly, so I divide the dataset into several groups based on their categories and calculate their IC components separately and then combine them.

The results are showed in Table 1.

Dataset \ Space	baseline	Original	PCA	ICA	LDA
ETH-80	0.125	0.84±0.05	0.84±0.04	0.78±0.10	0.80±0.02
CIFAR-10	0.100	0.40±0.04	0.37±0.03	0.34±0.07	0.38±0.02
AR (male, female)	0.500	0.81±0.03	0.84±0.02	0.77±0.10	0.97±0.01

Table 1: The average classification accuracy and error bounds in 5 times running under different spaces. The baseline is the random guess method. We can see that ICA has larger variance than other methods, perhaps it is because the *FastICA* algorithm can be influenced by the training and testing data greatly.

2 Generate Random Sample from GMM

After the estimation of the GMM, I can draw samples from it to generate the new sample images. If I want to draw a sample from the class k, the sample method is first draw sample j form the multinomial distribution with parameter $p = (P_k(1), \cdots, P_k(M))$, then draw a sample from the probability density funciton $p_k(x|j)$. Finally, I project them back to the original space. Some example results are showed in Figure 1.

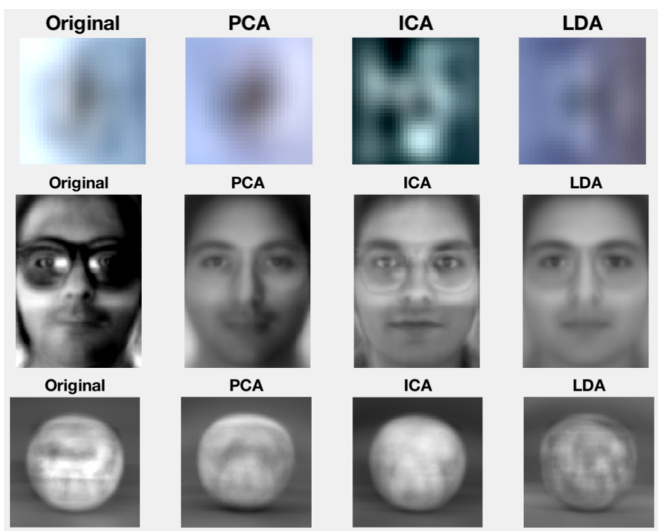

Figure 1: The random samples drew from the GMM in original space, PCA, ICA and LDA subspace. The first row is the flight in CIFAR-10 dataset. The second row is the male face in AR face dataset. The third row is the apple from ETH-80 dataset.

3 Discussion

Comparing with the project 1, I can see that GMM can achieve better classification results. I think the reason is each object has many different shapes or positions (e.g., wear glasses or not), and the GMM can allow us to estimate these differences. We can also see that the random samples from GMM allows us to catch some details of an object (e.g., the sunglasses) instead of just showing a sample around the mean likes the single Gaussian distribution model in project 2.