Image Recognition: Practical Application of Dimension Reduction

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Abstract

Pattern or image recognition is the ability of software to detect and identify objects of interest. Image recognition is relevant to a wide range fields and provides many useful applications in technology, like self driving cars and identity verification from iris code (https://nanonets.com/image-recognition/). The high-dimensionality of data required to produce recognizable images proves to be a significant difficulty toward image identification and analysis. Dimension reduction is a common solution to the challenges presented by analysis of such high dimensional data, and methods like Principal Component Analysis (PCA) are popular for enhancing image recognition while balancing computational and time costs. This study will assess methods of dimension reduction in facial image recognition.

Introduction

The method of dimension reduction in image recognition is a popular technique for analyzing high-dimensional data in a low-cost setting. Broadly, this study addresses the challenges presented by the high-dimensionality of imaging data toward recognition and identification of objects of interest. The objective of the study is to assess effectiveness of methods for detection and identification of facial images from dimensionally reduced data. I will assess two methods of dimension reduction, PCA and simple projection, by comparing the results of these methods toward the utilization of facial recognition. Given a set of facial images, I will detect and identify similarities of images between two sets of data to assess the effectiveness of methods by their respective abilities to accurately identify facial images.

Method

Two methods, PCA and simple projection, are utilized toward assessing the effectiveness of dimension reduction in facial image recognition. Each method is tested on ability to accurately identify facial images from two sets of data: training and testing data. Images in the training data set are labeled, and testing images are unlabeled; effectiveness of each method is assessed by its ability to accurately identify non-labeled images from the testing set and match them to images from the training set.

Projection is a method of dimension reduction which projects high-dimensional data into a lower-dimensional space with the goal of preserving key components of the original data, like variation and relative position. PCA is a highly effective method of projection in dimensionality reduction in which a vast majority of the variation in a set of data is captured by a significantly reduced vector through principal components. Training images are varied by expression, position, and other key qualities.

First, I project training images into a lower-dimensional subspace through each of the two methods. Reduced vectors represent different training images to be identified. Next, I classify the images by projecting reduced vectors from the test data and finding the column (representing an image) from the training set that is closest in distance, or its “nearest neighbor”. I assess the effectiveness of methods by testing their respective abilities to identify facial images from test data by attempting to classify images between each set, and comparing both the visual image, and the number of nearest neighbors, to the test image.

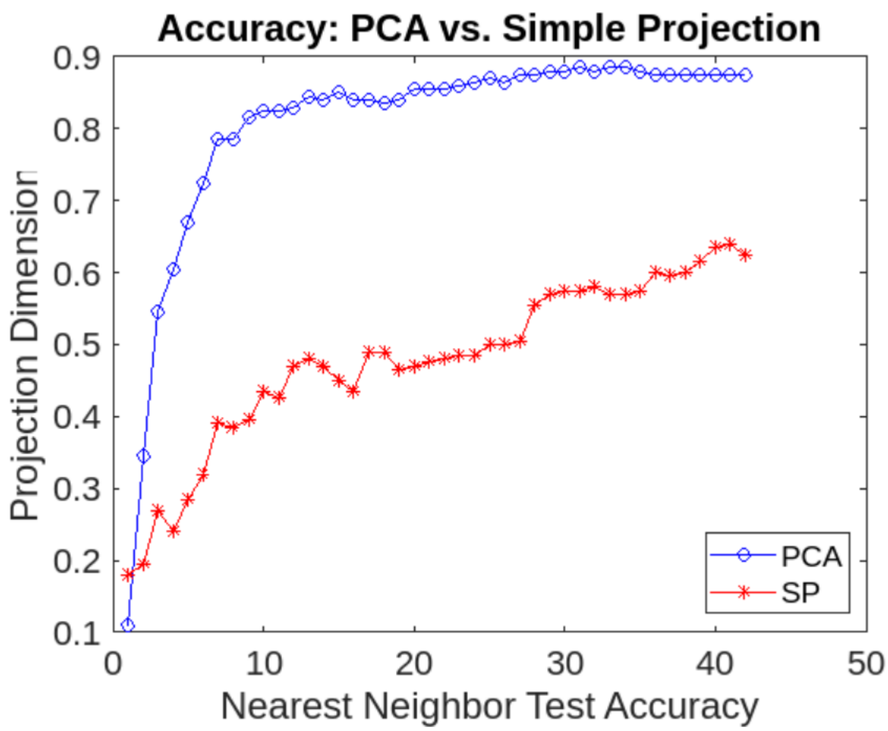
Program Code

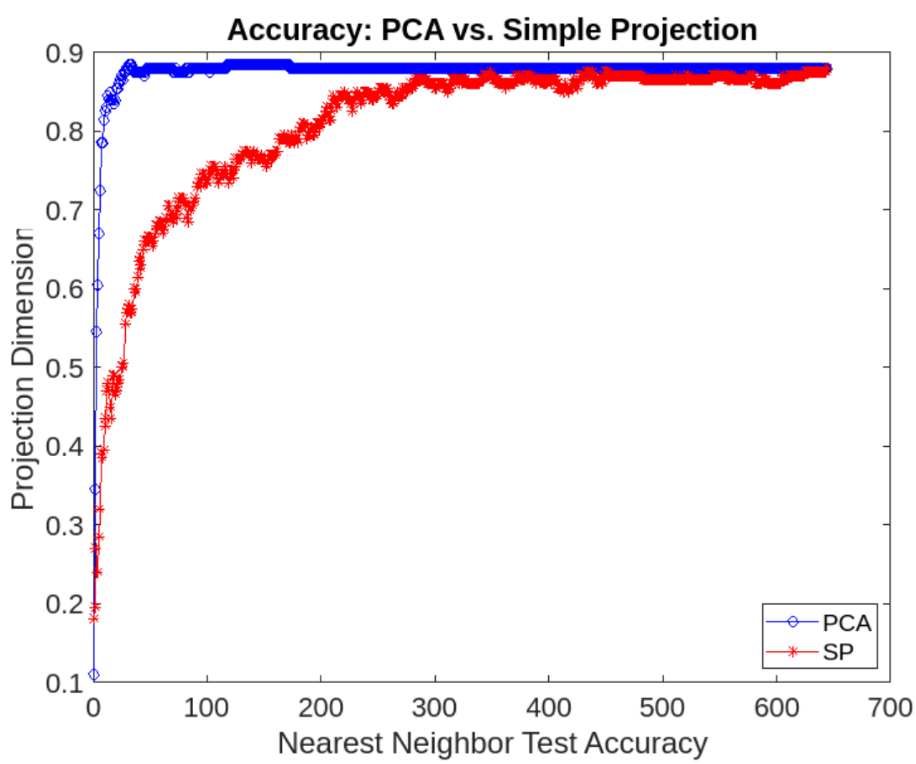
```
clear;

load mid_train.mat
load mid_test.mat

X = Ytrain';
[m, n] = size(X);

% PCA
C = cov(X);
```

```
[U, S, V] = svd(C);

K = 644;

for k = 1:K
    tic;
    U1 = U(:,1:k);
    Z_train = X*U1;
    Z_test = Ytest'*U1;

    % NN
    for i = 1:m
        for j = 1:m
            d(i,j) = norm(Z_test(i,:)-Z_train(j,:));
        end
        [dis, dis_ind] = sort(d(i,:));
        nn(i) = dis_ind(1);
    end

    % Accuracy
    acc_pca(k) = sum(ceil(nn/5) == ceil((1:m)/5))/m;
    y(k) = toc;
end
toc

tic;
% SP
for k = 1:K
    Z_train_sp = Ytrain(1:k,:)';
    Z_test_sp = Ytest(1:k,:)';

    % NN
    for i = 1:m
        for j = 1:m
            d_sp(i,j) = norm(Z_test_sp(i,:)-Z_train_sp(j,:));
        end
        [dis, dis_ind] = sort(d_sp(i,:));
        nn_sp(i) = dis_ind(1);
    end

    % Accuracy
    acc_sp(k) = sum(ceil(nn_sp/5) == ceil((1:m)/5))/m;
end
toc;

plot(1:K, acc_pca, 'bo-', 1:K, acc_sp, 'r*-');
```

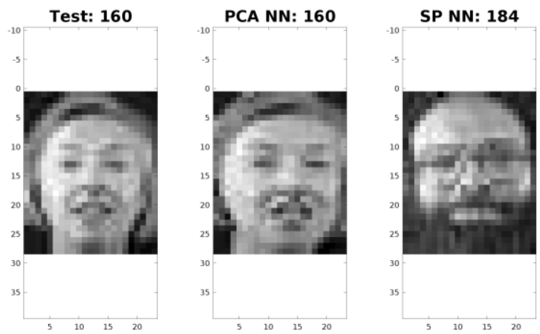
```
legend('PCA', 'SP', 'location', 'southeast');
set(gca, 'fontsize', 16);
ind = [ceil(nn/5) == ceil((1:m)/5); ceil(nn_sp/5) == ceil((1:m)/5)];
title('Accuracy: PCA vs. Simple Projection')
xlabel('Nearest Neighbor Test Accuracy')
ylabel('Projection Dimension')

S = [160 135 5 75];

for j = 1:4
    figure(j+10); clf;
    set(gcf, 'position', [50, 50, 700, 400]);

    subplot(1,3,1);
    I = reshape(Ytest(:,S(j)),28,23);
    imagesc(I);
    colormap(gray);
    axis equal;
    title(['Test: ' num2str(S(j))], 'fontsize', 20);

    subplot(1,3,2);
    I = reshape(Ytrain(:,nn(S(j))),28,23);
    imagesc(I);
    colormap(gray);
    axis equal;
    title(['PCA NN: ' num2str(nn(S(j)))], 'fontsize', 20);

    subplot(1,3,3);
    I = reshape(Ytrain(:,nn_sp(S(j))),28,23);
    imagesc(I);
    colormap(gray);
    axis equal;
    title(['SP NN: ' num2str(nn_sp(S(j)))], 'fontsize', 20);
end
```

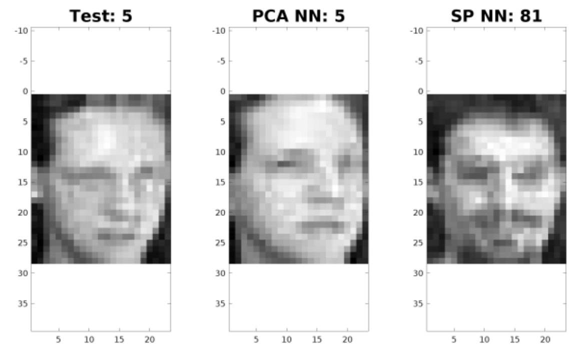
Results

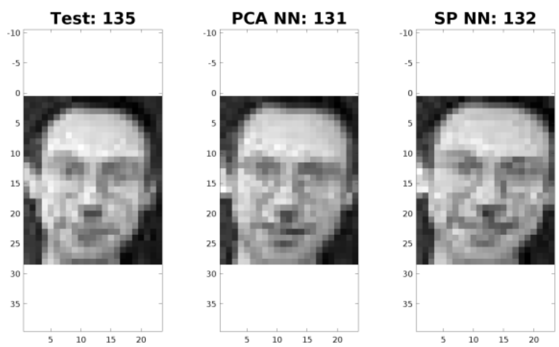

Accuracy: PCA vs. Simple Projection
Projection Dimension
Nearest Neighbor Test Accuracy
PCA
SP
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
10
20
30
40
50

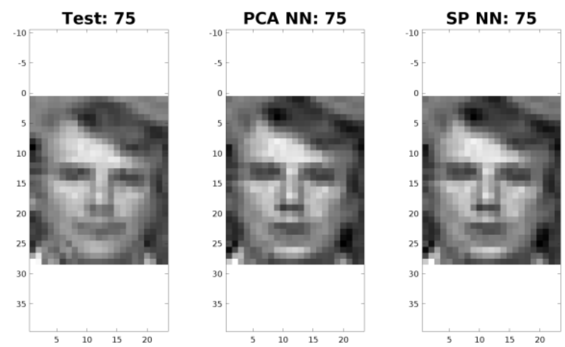

Accuracy: PCA vs. Simple Projection
Projection Dimension
Nearest Neighbor Test Accuracy
PCA
SP
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
100
200
300
400
500
600
700

K = 40:

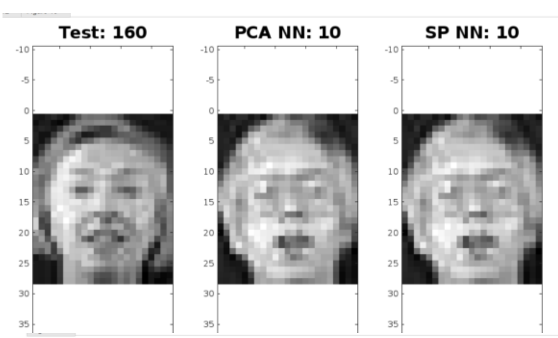

Test: 160
PCA NN: 160
SP NN: 184

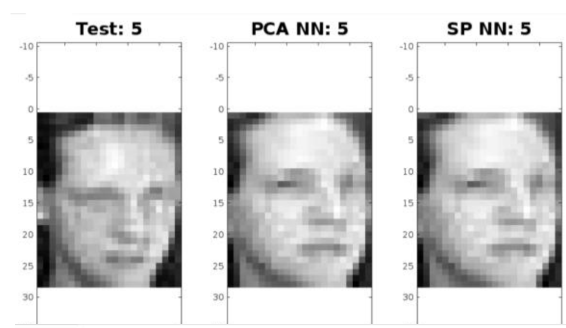

Test: 5
PCA NN: 5
SP NN: 81

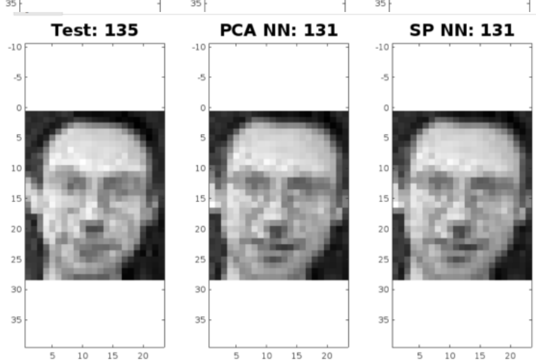

Test: 135
PCA NN: 131
SP NN: 132

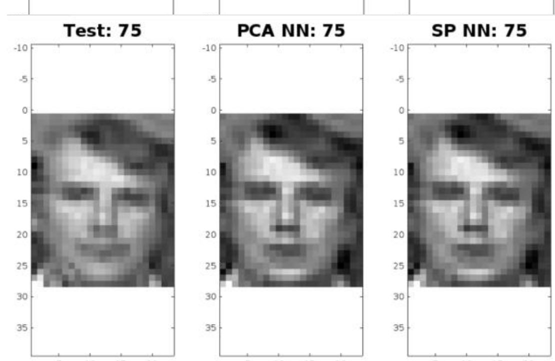

Test: 75
PCA NN: 75
SP NN: 75

K = 644:


Test: 160
PCA NN: 10
SP NN: 10


Test: 5
PCA NN: 5
SP NN: 5


Test: 135
PCA NN: 131
SP NN: 131


Test: 75
PCA NN: 75
SP NN: 75

Conclusions

Using a smaller k (k = 40), PCA was both highly accurate and efficient in identifying facial images, with only a single complete failure. Similarly, simple projection performed well for large k (k = 644). However, PCA still performed relatively well at a high dimension, while simple projection was not as accurate at a lower dimension. At k = 40, PCA accurately identified all four people, but with slightly different facial expressions. Simple projection misidentified two. At k = 644, PCA and simple projection each misidentified two, and matches have varied facial expression. The sample size is small, so it may be difficult to draw strong conclusions regarding the overall accuracy of projection on mid- to lower-dimensional data from the scope of this study.

Observing the accuracy plot at k = 40, it is clear that PCA has significantly higher accuracy. This plot would suggest PCA is considerably more accurate as a method of dimension reduction. However, when the accuracy is measured across all 644 dimensions, it is clear that the accuracy of simple projection converges to the accuracy of PCA given a high-dimensional subspace at roughly k =300. Speed of processing is very fast for PCA at a low dimension, but time costs increase exponentially with dimension. Since the accuracy converges at a high dimension, projection is preferred for high-dimensional data, as computational costs are comparatively low at high dimensions. Results support the assertion that PCA is extremely accurate and effective in handling relatively low-dimensional data, while projection is a highly effective method of processing very high-dimensional data with low computational and time costs.