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| **Eigenface Project** |
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| **Programming Assignment 3** |
| **Computer Science 679 – Pattern Recognition, UNR, Dr. Bebis** |
| **Due: Monday March 23, 2015** |
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# Abstract

This paper describes our research regarding the third class project for the Computer Science pattern recognition class CS 679 taught by Dr. Bebis who is Department Chair of the Computer Science Department at the University of Nevada in Reno, Nevada.

The primary topics included in the main body of this report are a description of the project, linear algebra and eigenvectors, eigenface theory from eigenvectors, and approach to eigenface recognition.

# Technical Discussion

## Eigenvectors and eigenvalues

Eigenvectors are those vectors that are invariant in direction to the action of a matrix A on the vector as follows:

|  |  |  |
| --- | --- | --- |
|  |  | (1) |

In the above, is a square nxn matrix, is an nx1 vector, and is a scalar. As mentioned above, the action of the matrix upon the vector is to scale, and to only scale, the vector and not to change the direction of the vector

## Eigenfaces

The eigenface approach taken and experimented in this paper is from the research of Turk and Pentland,[[1]](#footnote-1) and their work was motivated by the earlier works of Sirovich and Kirby who represented pictures using principal component analysis.[[2]](#footnote-2) Principal component analysis is a least squares approach for minimizing the error associated with a projection of the data onto a different basis.

Given a vector in an N dimensional space, it can be represented by a set of N orthogonal basis vectors as follows

|  |  |  |
| --- | --- | --- |
|  |  | (2) |

The goal is to find an N x K transformation matrix U such that

|  |  |  |
| --- | --- | --- |
|  |  | (3) |

Where is an Nx1 rasterized image

|  |  |  |
| --- | --- | --- |
|  |  | (4) |

And the basis vectors the right side of the equation are the standard basis (natural or canonical) vectors of Euclidean space as follows:

|  |  |  |
| --- | --- | --- |
|  |  | (5) |

Where is known as the Kronecker delta function

|  |  |  |
| --- | --- | --- |
|  |  | (6) |

Yielding a set of basis vectors as follows

|  |  |  |
| --- | --- | --- |
|  |  | (7) |

Moreover, the vector can be represented by a set of K orthogonal basis vectors *i*=1,…,K in a lower K (K<N) dimensional space, and each vector is an Nx1 vector. The lower K (K<N) dimensional space as

|  |  |  |
| --- | --- | --- |
|  |  | (8) |

Principal component analysis selects the basis and coefficients to minimize the error

|  |  |  |
| --- | --- | --- |
|  |  | (9) |

# Project

This project consists of several experiments to compare various versions of the eigenface recognition algorithm on different data sets.

## Training and software validation

To ensure the eigenface program works correctly, we were asked to project an image from the training data set onto the eigen-space, reconstruct it from the full set of eigenfaces, and then compute the error between the original image and the reconstructed image. Our selected input image and the reconstructed image is shown in Figure 1. The reconstruction error is

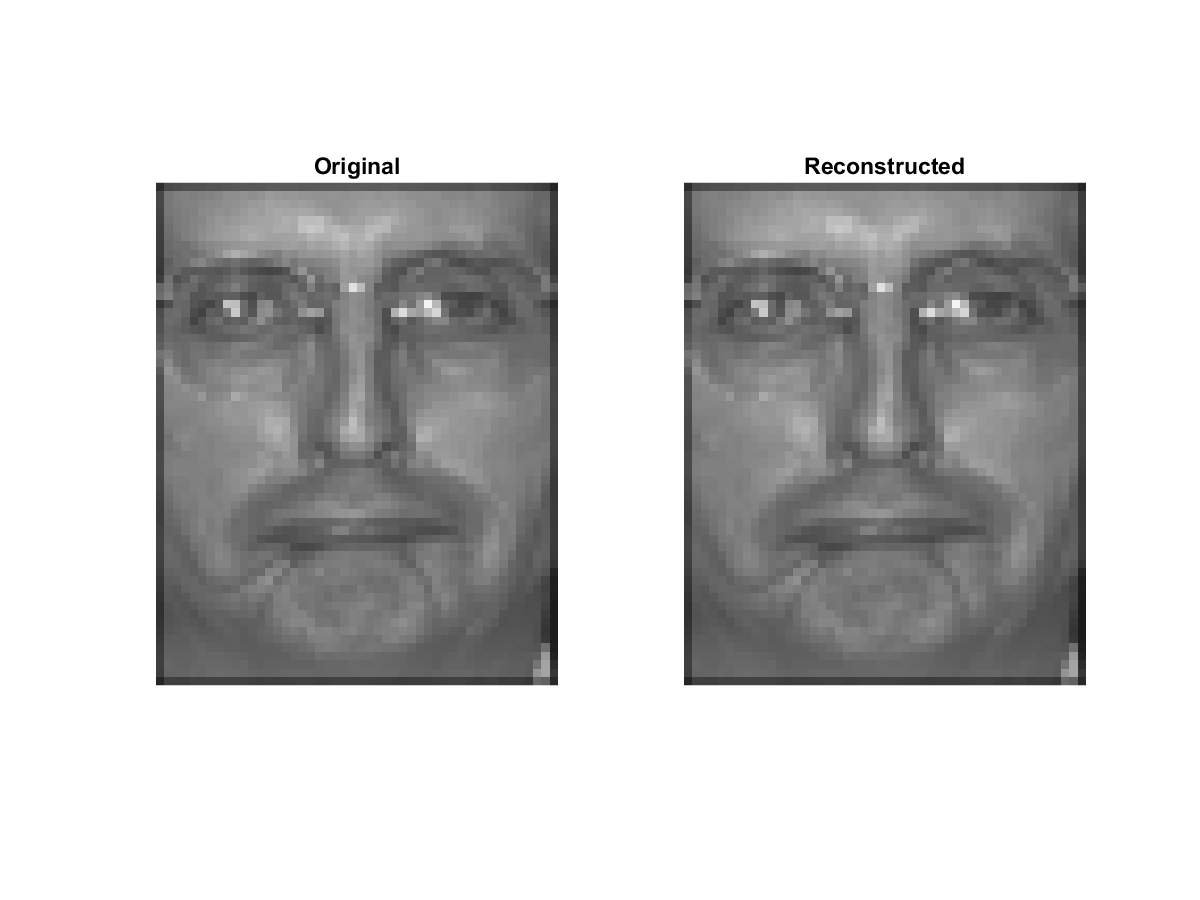


Figure 1: Original input image and reconstructed image from eigenfaces

## Experimental Results

In the first experiment, we are asked to use fa\_H (frontal image, high resolution) for training and fb\_H (alternate frontal image, high resolution) for testing.

### Hi resolution a.I with 80% information

We run the experiments a.I through a.IV with information content being 80%. With the training, we compute the average face and then the eigenfaces of the 1204 images (with 867 subjects). We then display the average face along with the eigenfaces corresponding to the top ten largest eigenvalues.

The average face is shown in Figure 2.



Figure 2: Average face

The ten eigenfaces corresponding to the ten largest eigenvalues are shown in Figure 3.

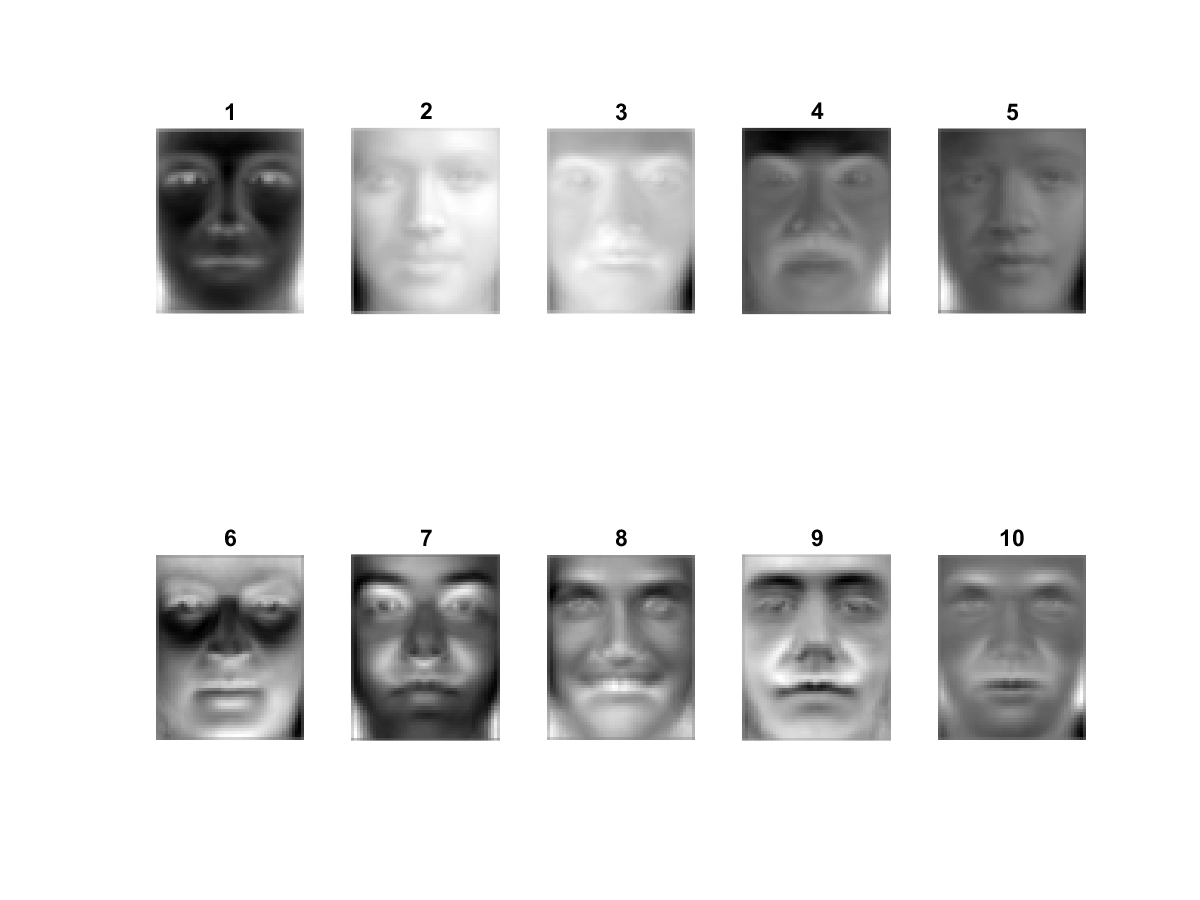


Figure 3: Eigenfaces for the ten largest eigenvalues (in decreasing order)

The ten eigenfaces corresponding to the ten smallest eigenvalues are shown in Figure 4.

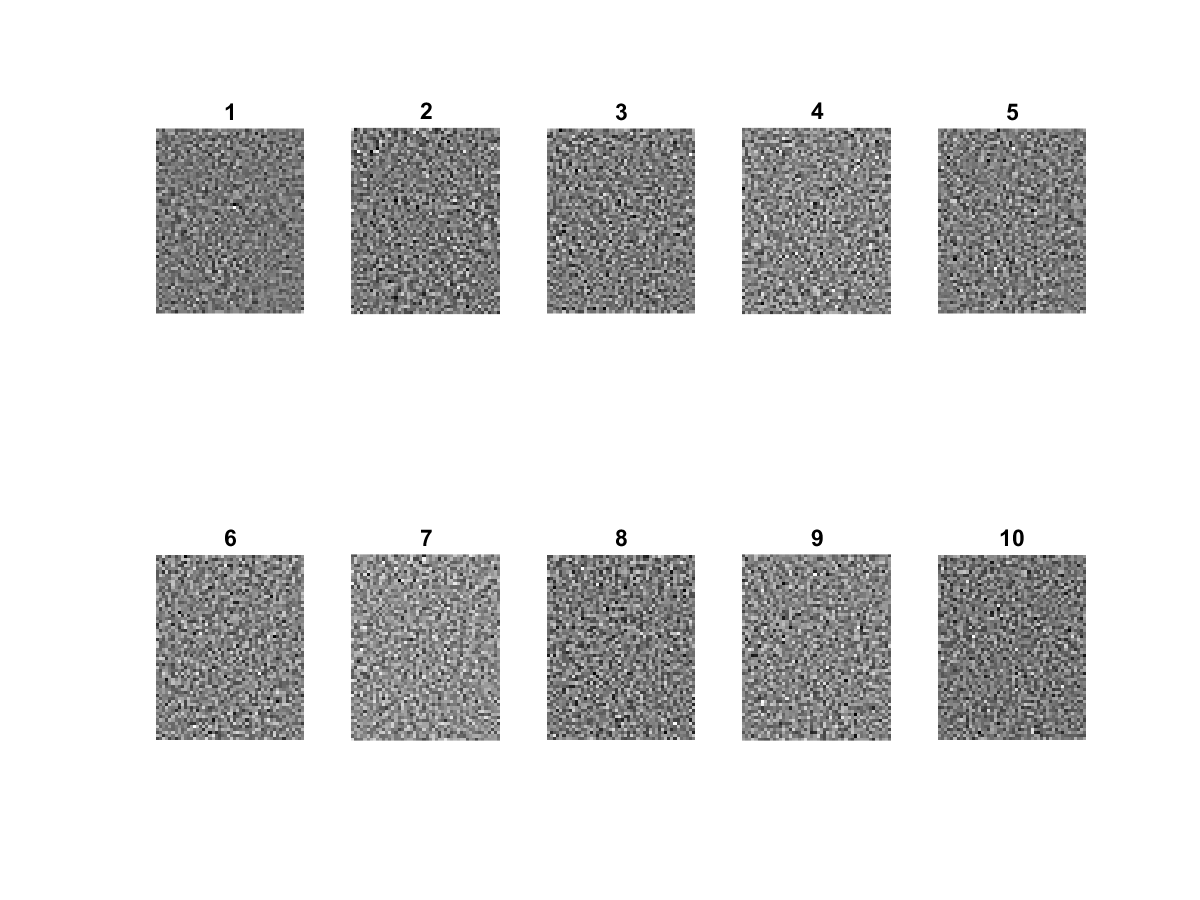


Figure 4: Eigenfaces (noise) for the ten smallest eigenvalues (in decreasing order)

### Hi resolution a.II to a.IV with 80% information

In this experiment, we chose the top eigenvectors (eigenfaces) that will preserve 80% of the information in the imagery based on the basis sets, and we project the training images onto the 80% basis set. We then compute the Mahalanobis distance between the eigen-coefficient vectors for each pair of training and query images to determine the match distance. We then chose the top N images having the highest similarity score with the query image and if the query image is among the N most familiar faces retrieved then it is a true positive or a match. We plot the Cumulative Match Characteristic Curve in Figure 5, the correctly matched images in Figure 6 along with training, and the incorrectly matched in Figure 7 along with the training.

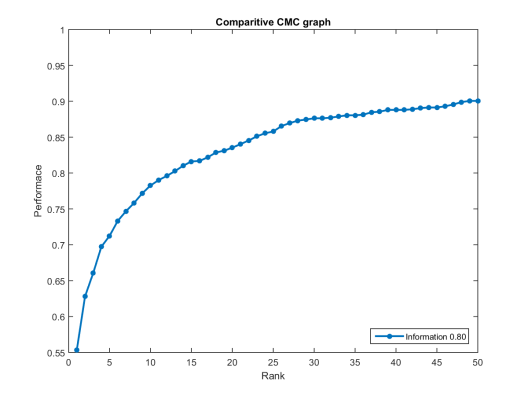


Figure 5: CMC given 80% information

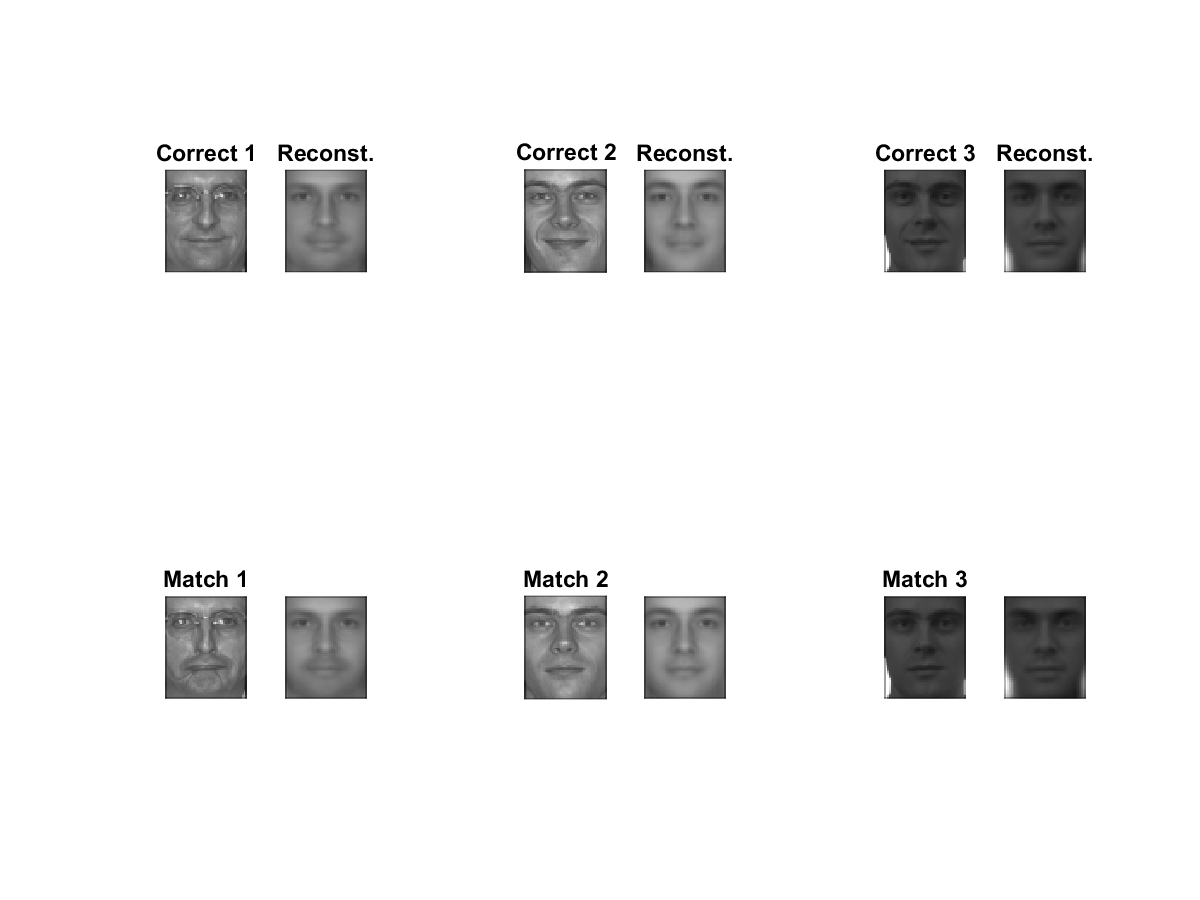
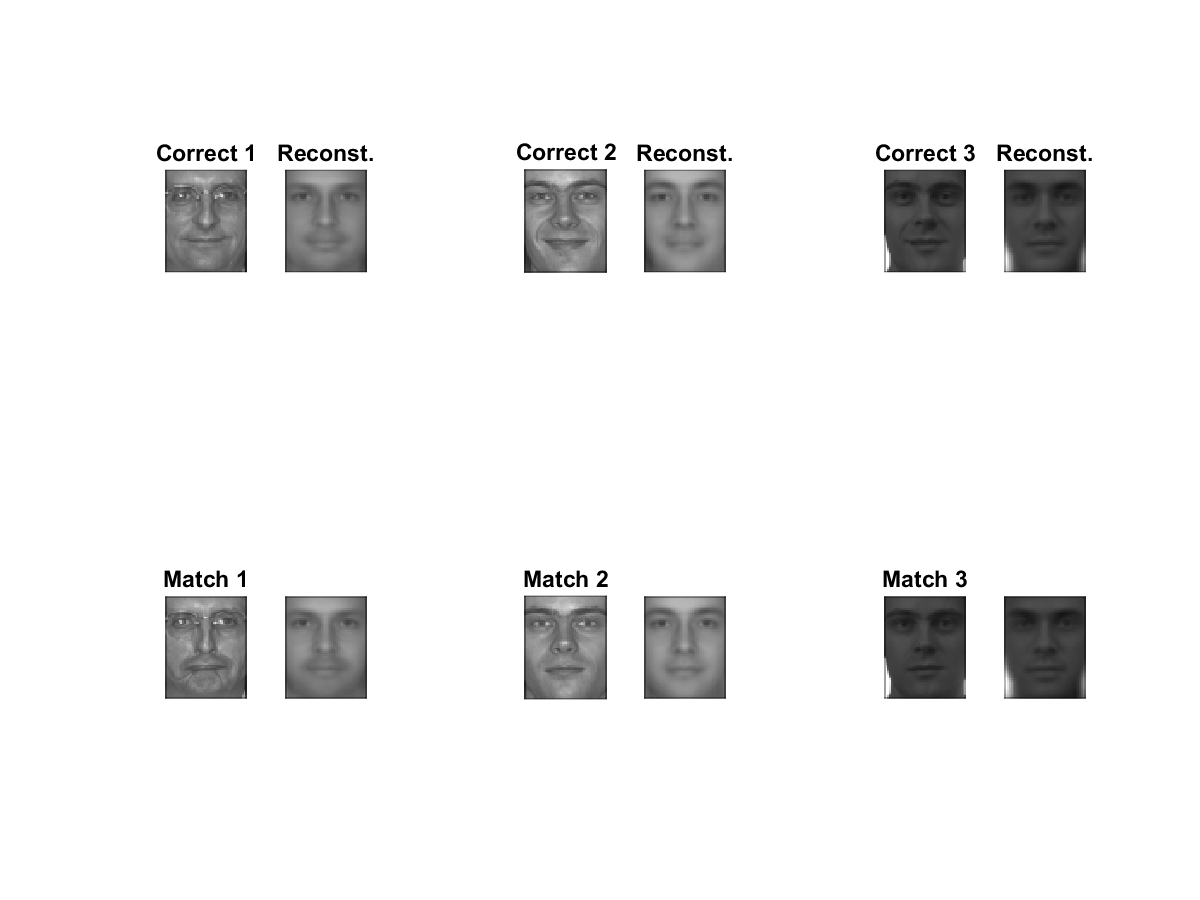
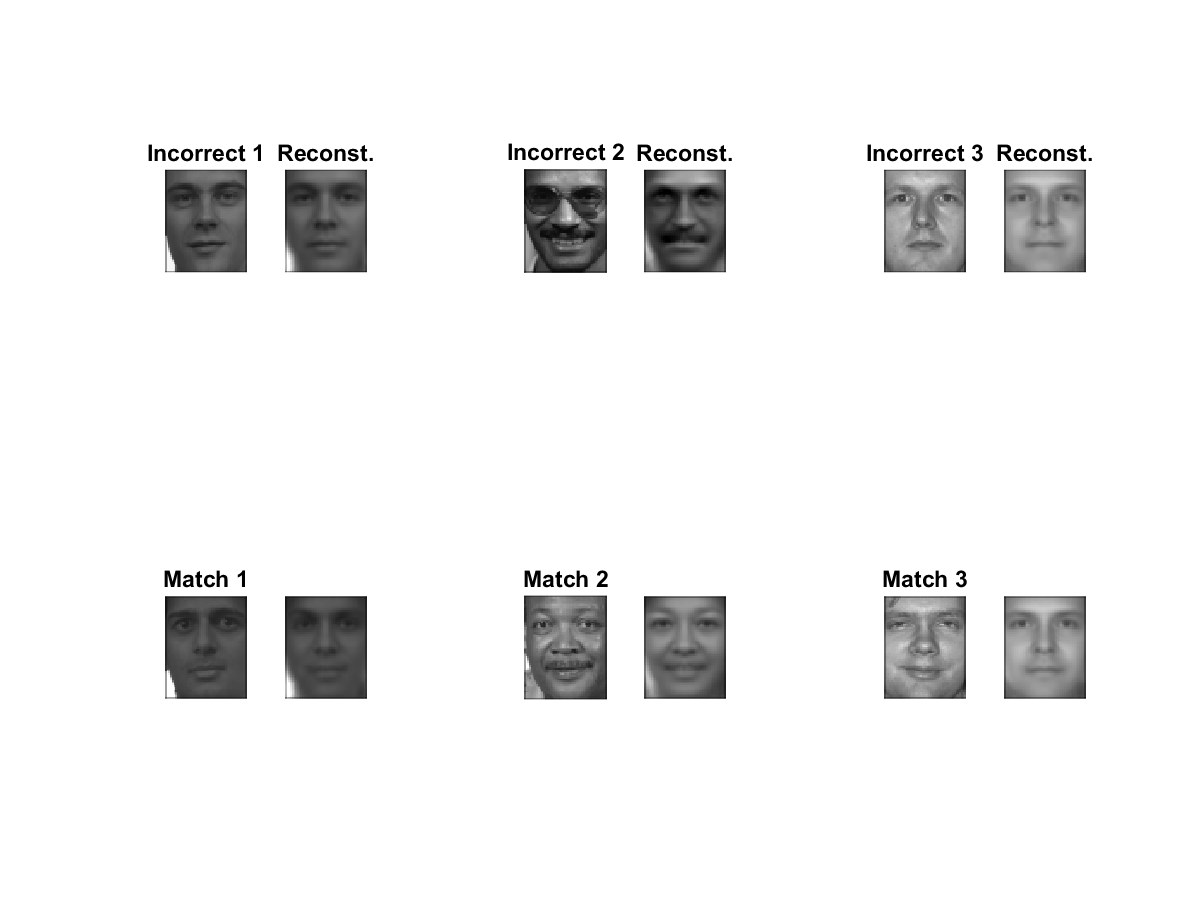
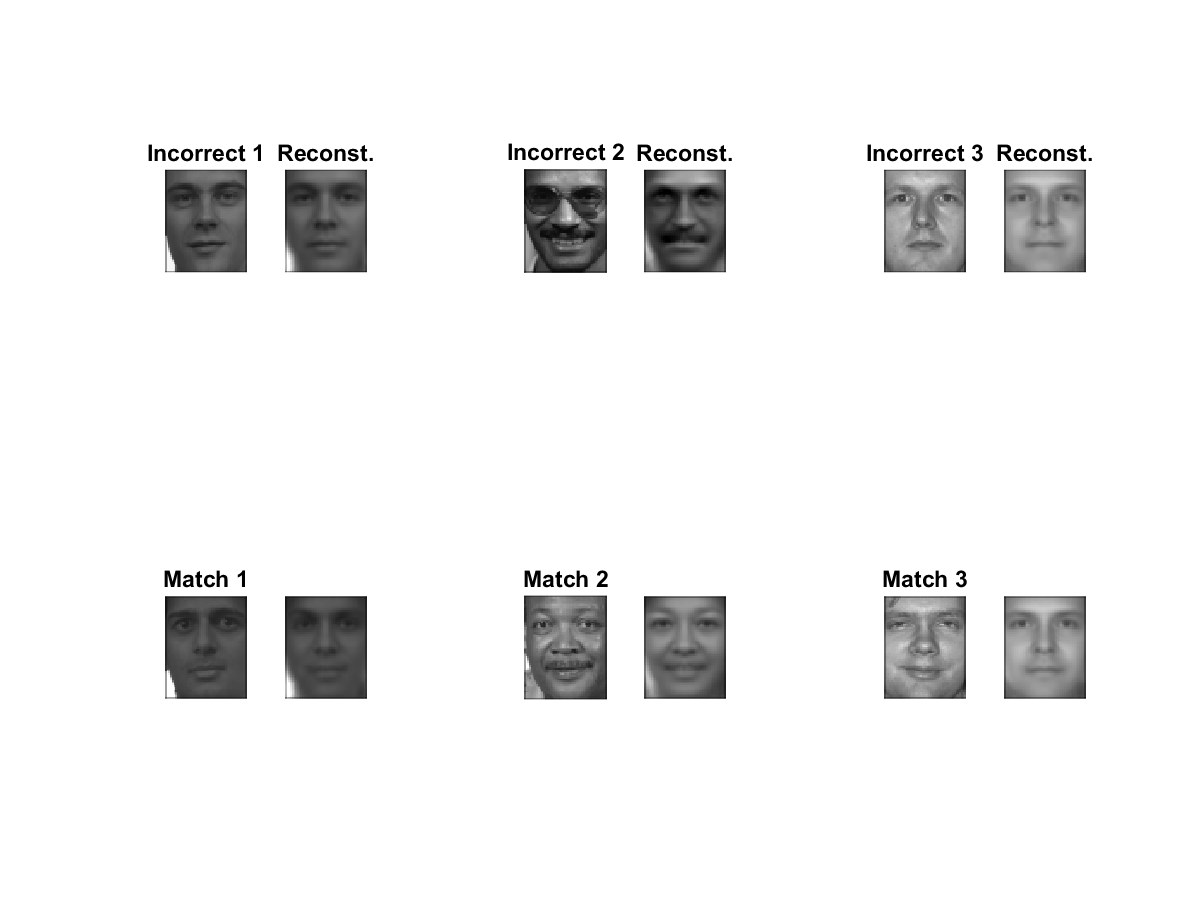


Figure 6: Correctly matched faces, the training faces, and their reconstructions.

Figure 7: Incorrectly matched faces, the training faces, and their reconstructions.



### Hi resolution a.II to aIV with 90 % information

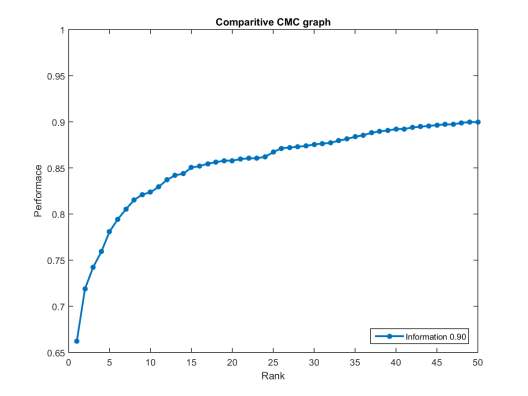
In this experiment, we chose the top eigenvectors (eigenfaces) that will preserve 90% of the information in the imagery based on the basis sets, and we project the training images onto the 90% information basis set. We then compute the Mahalanobis distance between the eigen-coefficient vectors for each pair of training and query images to determine the match distance. We then chose the top N images having the highest similarity score with the query image and if the query image is among the N most familiar faces retrieved then it is a true positive or a match. We plot the Cumulative Match Characteristic Curve in Figure 8, the correctly matched images in Figure 9 along with training, and the incorrectly matched in Figure 10 along with the training.

Figure 8: CMC given 90% information

Figure 9: Correct matching images, training images, and reconstructions

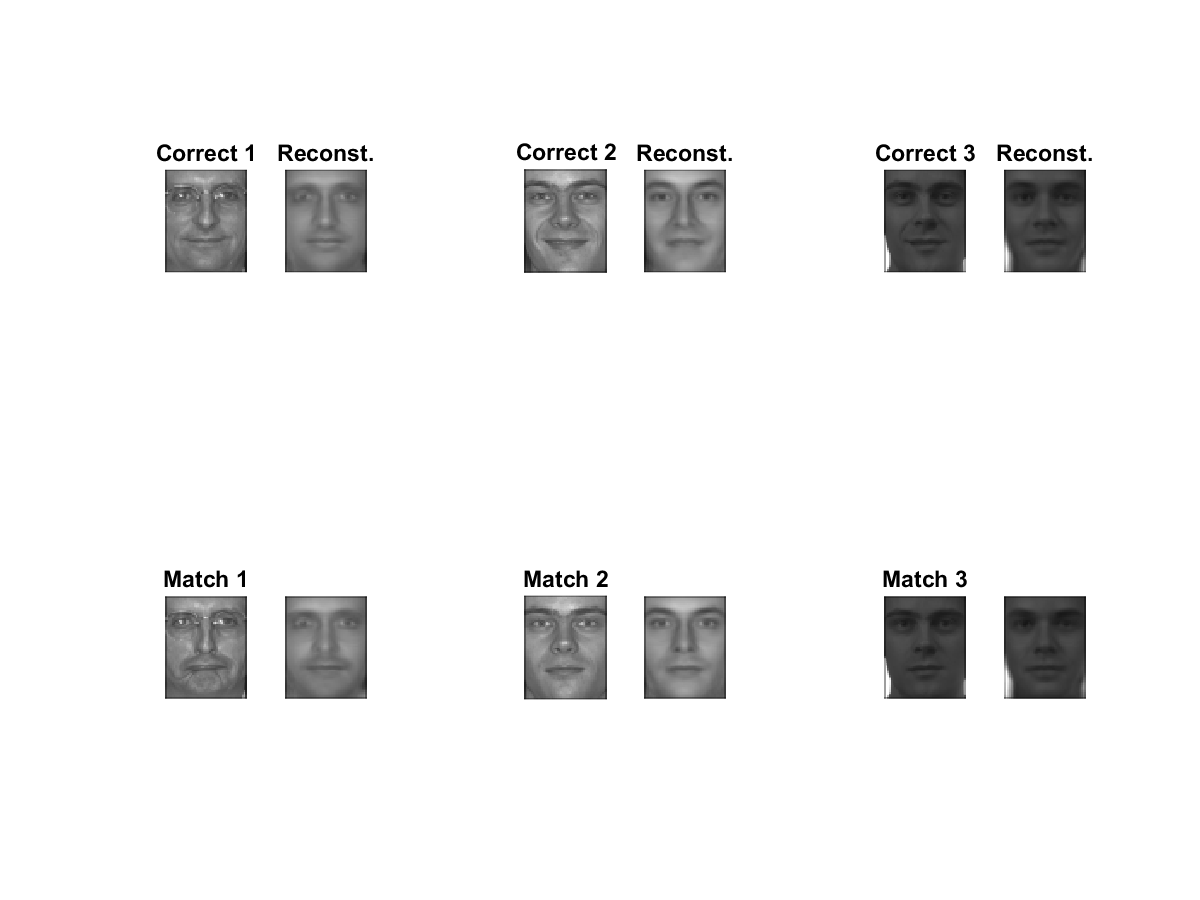
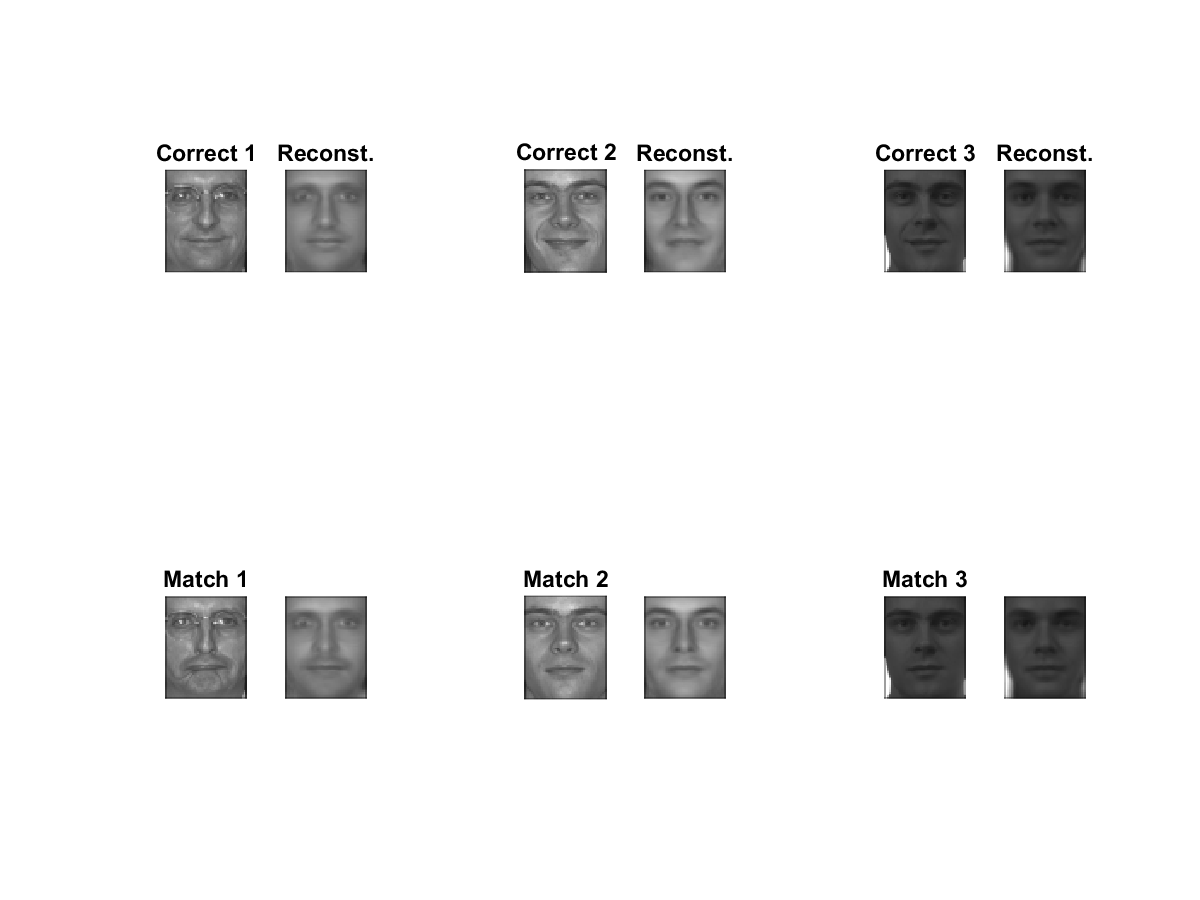
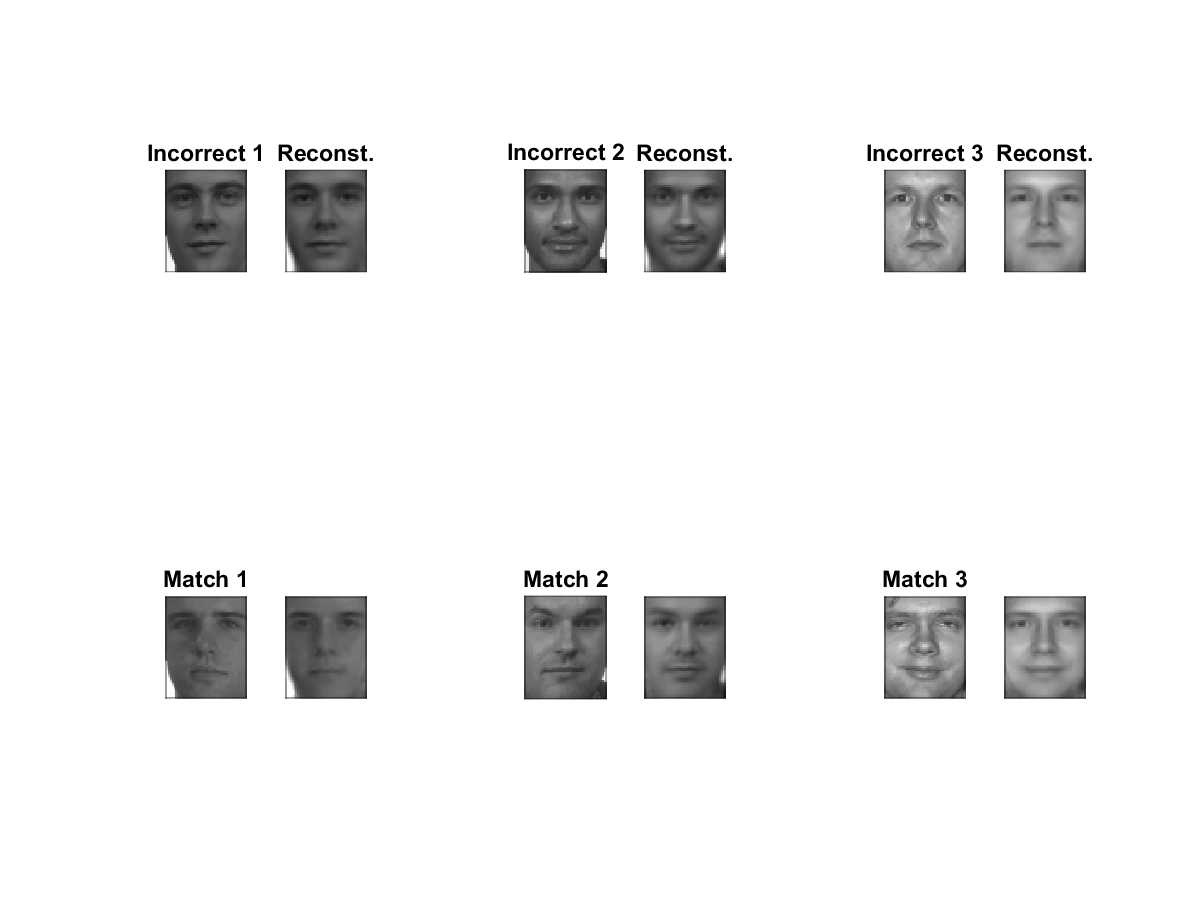
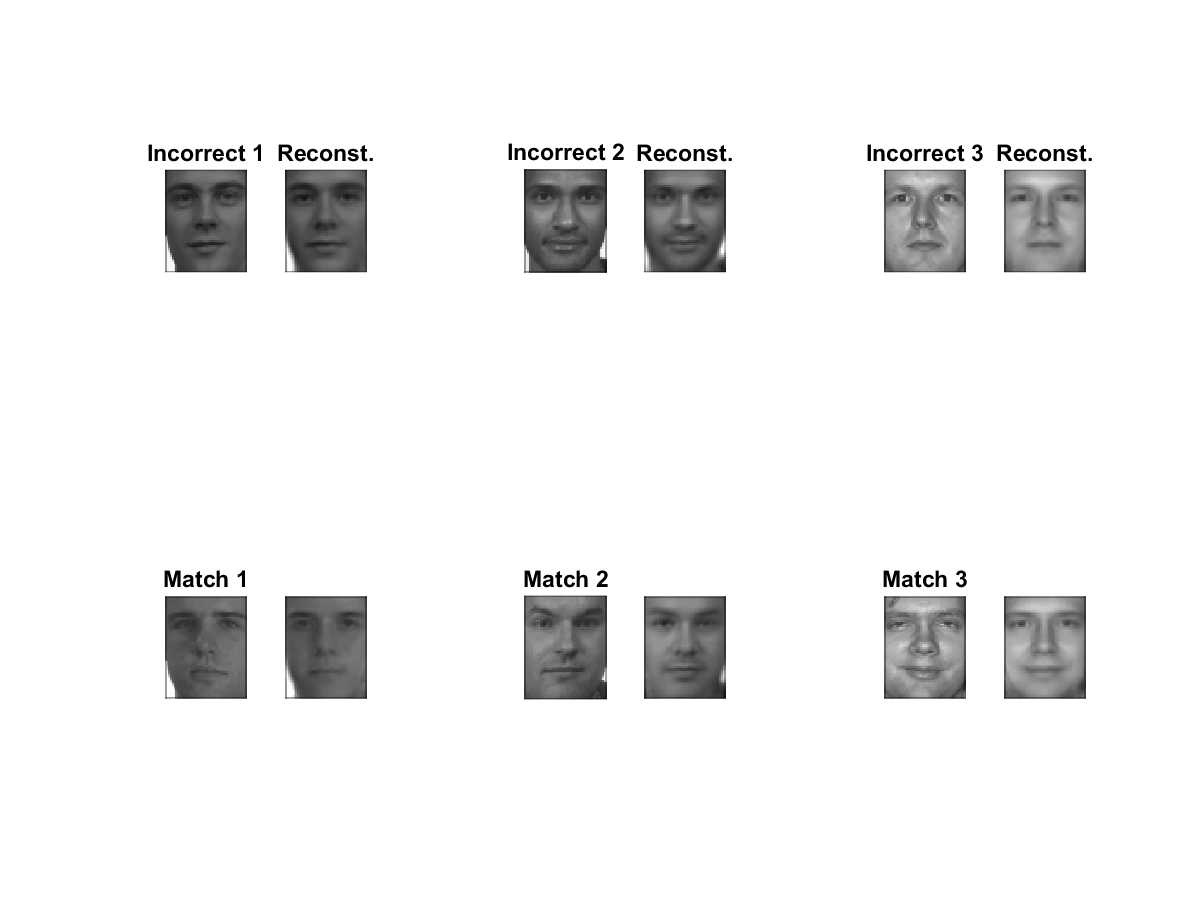


Figure 10: Incorrect matching images, training images, and reconstructions



### Hi resolution a.II to aIV with 95 % information

In this experiment, we chose the top eigenvectors (eigenfaces) that will preserve 95% of the information in the imagery based on the basis sets, and we project the training images onto the 95% basis set. We then compute the Mahalanobis distance between the eigen-coefficient vectors for each pair of training and query images to determine the match distance. We then chose the top N images having the highest similarity score with the query image and if the query image is among the N most familiar faces retrieved then it is a true positive or a match. We plot the Cumulative Match Characteristic Curve in Figure 12, the correctly matched images in along with training, and the incorrectly matched in along with the training.

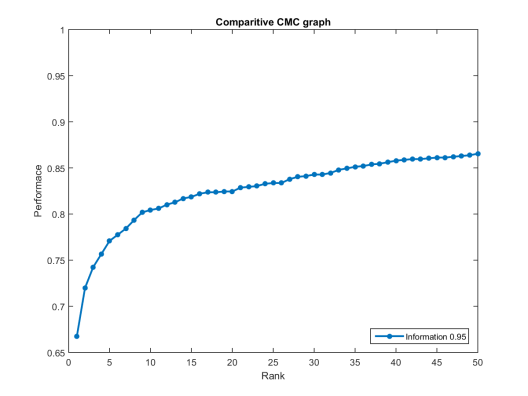


Figure 12: CMC for 95% information

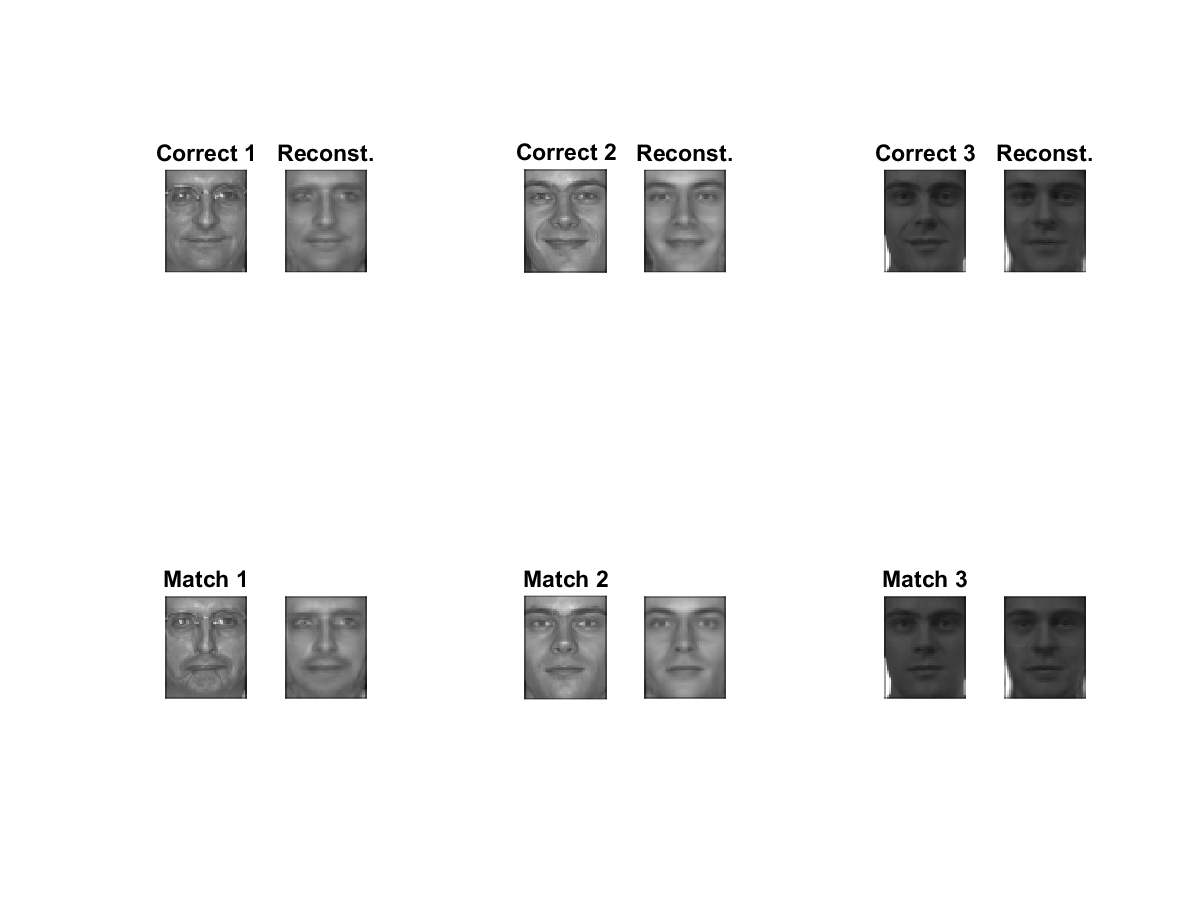
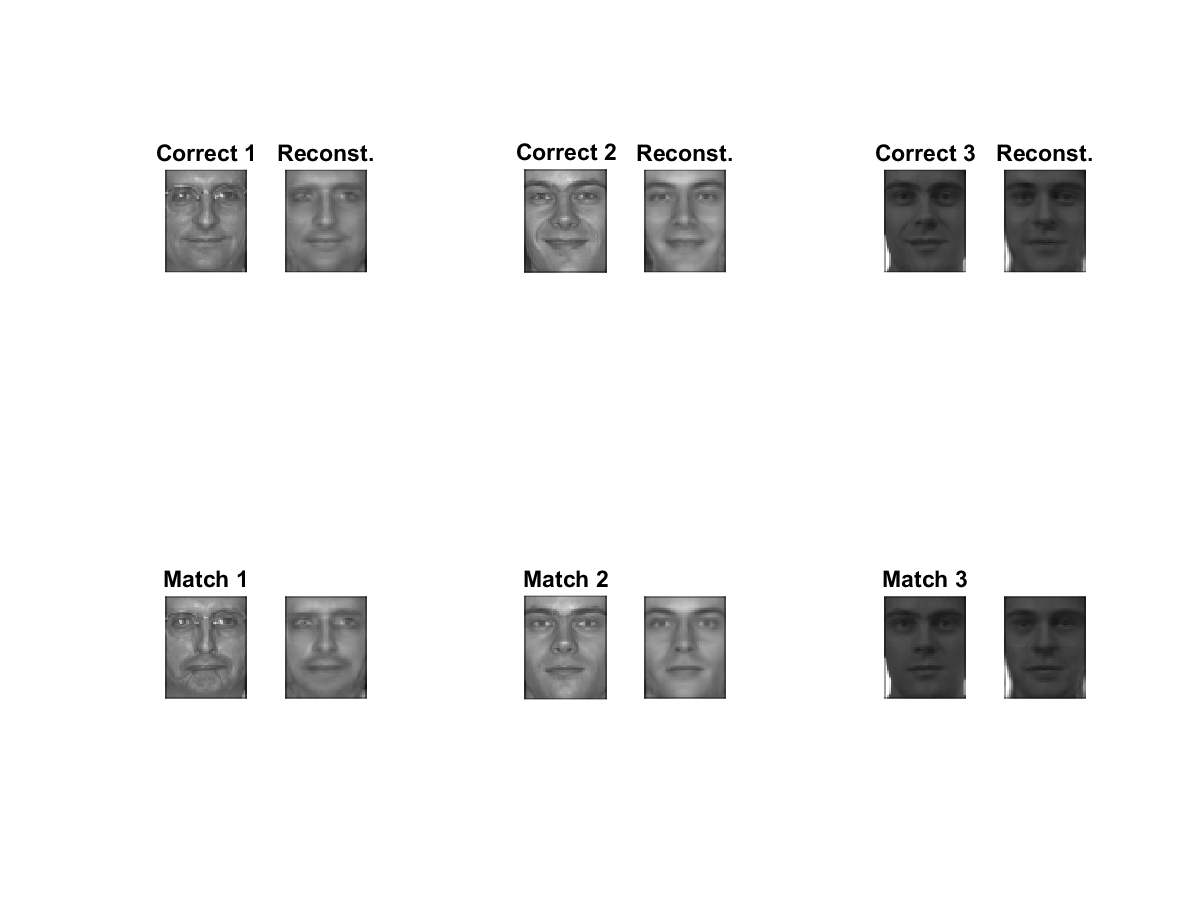
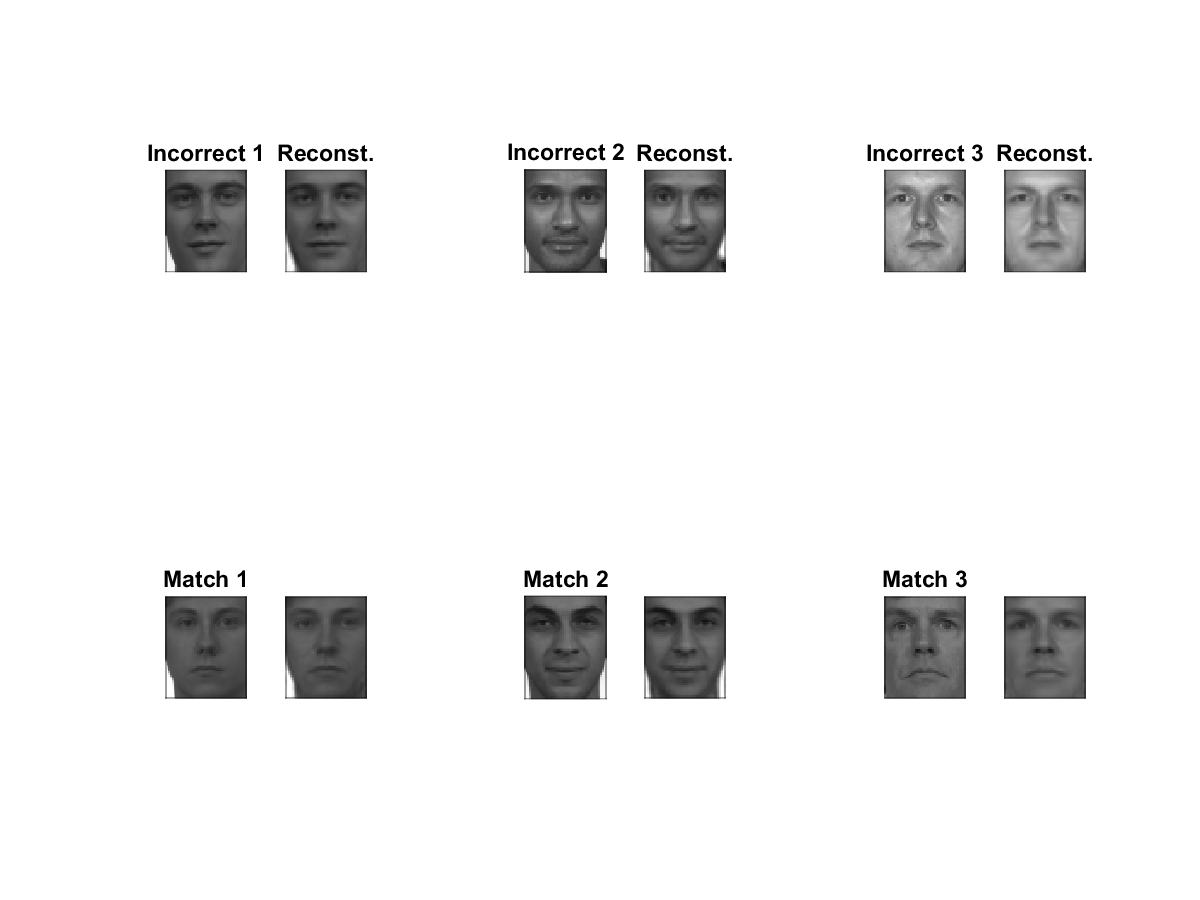
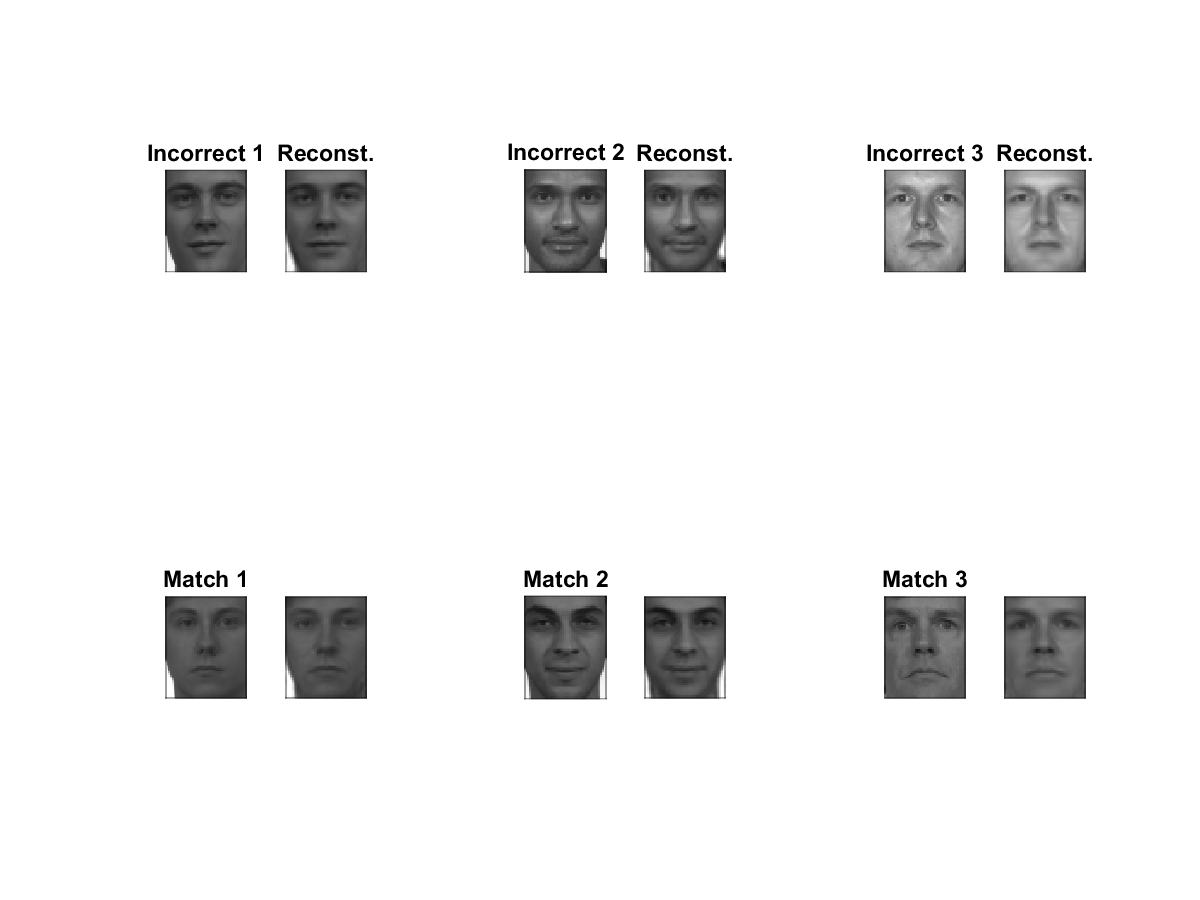


Figure 13



### Lo resolution a.I with 80% information

In this experiment, we chose the top eigenvectors (eigenfaces) that will preserve 80% of the information in the imagery based on the basis sets, and we project the training images onto the 80% basis set. We then compute the Mahalanobis distance between the eigen-coefficient vectors for each pair of training and query images to determine the match distance. We then chose the top N images having the highest similarity score with the query image and if the query image is among the N most familiar faces retrieved then it is a true positive or a match. We plot the Cumulative Match Characteristic Curve in Figure 5, the correctly matched images in Figure 6 along with training, and the incorrectly matched in Figure 7 along with the training.

### Lo resolution a.II to a.IV with 80% information

### Lo resolution a.II to a.IV with 90% information

### Lo resolution a.II to a.IV with 95% information

# Conclusion

## Part a for face recognition

## Part b for intruder detection

# Contributors

Josh Gleason and Rod Pickens each wrote their own MATLAB software to perform the classification, the maximum likelihood estimation, the error estimation, the calculation of the Bayes error using false negative and false positive rates.

Josh generated the maximum likelihood performance charts and the variance of the classifier performance, and Rod generated the face detection performance charts. Josh generated the combined probability charts. Josh and Rod ensured that their individual programs gave identical results.

Josh wrote the theory section on maximum likelihood along with the results section, and he wrote the classifier section. Josh also did the experiments to evaluate the errors in the classifiers using different number of training examples.

Rod Pickens wrote the theory section on face detection along with the results section, and he wrote the appendix section on performance characteristics. Josh was very helpful to Rod in discussing and clarifying concepts with respect to performance characteristics, such as FPR, FNR, and Bayes error.

In all, both authors felt that this project was challenging and very educational.

# Appendix

1. M. Turk and A. Pentland, “Eigenfaces for Recognition,” Journal of Cognitive Neuroscience, vol. 3, no. 1 pp. 71-86, 1991. [↑](#footnote-ref-1)
2. L Sirovich and M Kirby, “Low-dimensional procedure for the characterization of human faces,” Journal of the Optical Society of America A, 4(3), 519-524. [↑](#footnote-ref-2)