# Image Preprocessing and Complete 2DPCA on Feature Extraction


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## INTRODUCTION

Gender recognition is becoming increasingly important in today's society. With its applications in biometric security, surveillance, and customer statistics collection, the balance between computational accuracy and efficiency is crucial. Recognizing gender from face images is particularly challenging in computer vision because it depends entirely on the quality of the face image. Therefore, regularity between pose and illumination is important for optimization.

This research included preprocessing the images from the given dataset to reduce variability, applying different feature extraction techniques, and employing Complete 2DPCA on the resulting images. The goal was to see which feature extraction technique optimized the performance of Complete 2DPCA while also paying attention to computation time.

## DATASET: MORPH-II

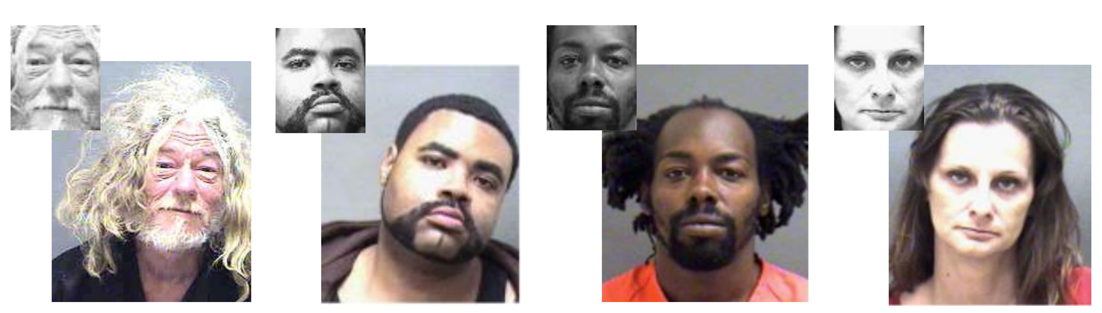
The academic release of the Craniofacial Morphology Database (MORPH-II) contains 55,134 unique mugshots from over 13,000 subjects [1].

- 16 – 77 years old
- Average of 4 images per person
- Unbalanced nature between race and gender

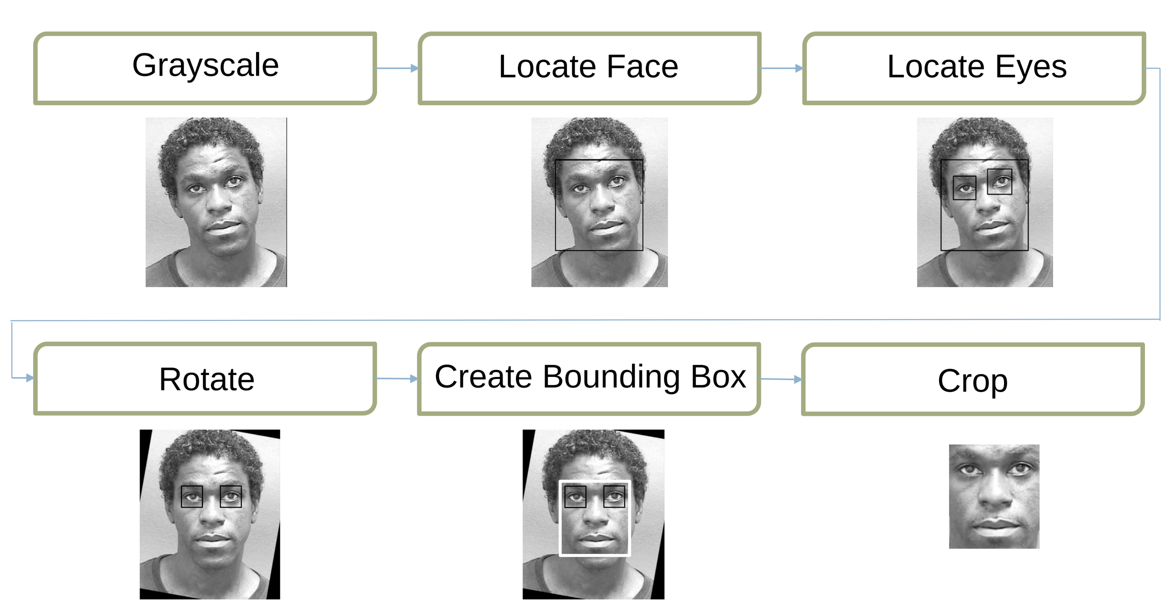
| | Total Images |
|---|---|
| **Male** | 46,644 |
| **Female** | 8,490 |
| **Total** | 55,134 |

## PREPROCESSING

Since this research centered around classification accuracies, uniformity of the data was necessary. There was a serious need to preprocess the MORPH-II images due to the high variation within pose, illumination, and scale from one image to the next.



In order to minimize variability, the following pipeline shows the steps taken to obtain the desired 70 x 60 pixel cropped images.




This process was implemented in python with the OpenCV package. Preliminary results showed this process increased accuracy rates.

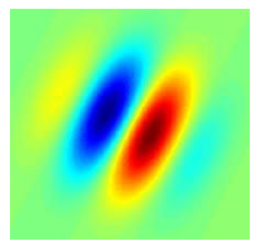
## FEATURE EXTRACTION

Feature extraction begins with image pixel values and builds features that summarize the original image in informative ways. These features are used to facilitate subsequent steps in classification algorithms. The particular extraction techniques used in my research were Local Binary Patterns (LBP), Gabor Filters, Gaussian Blurs, and Bio-Inspired Features. Which are all explained below:

**GAUSSIAN BLUR:** Blurring an image with Gaussian function results in reduction of image noise and detail by transforming each pixel. For my research I sharpened the blurred image for crisp edges.

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}$$

**GABOR FILTER:** A Gabor Filter is a linear filter used for texture analysis by looking at the frequencies and orientations of an image. It is useful in edge detection over multiple scales.

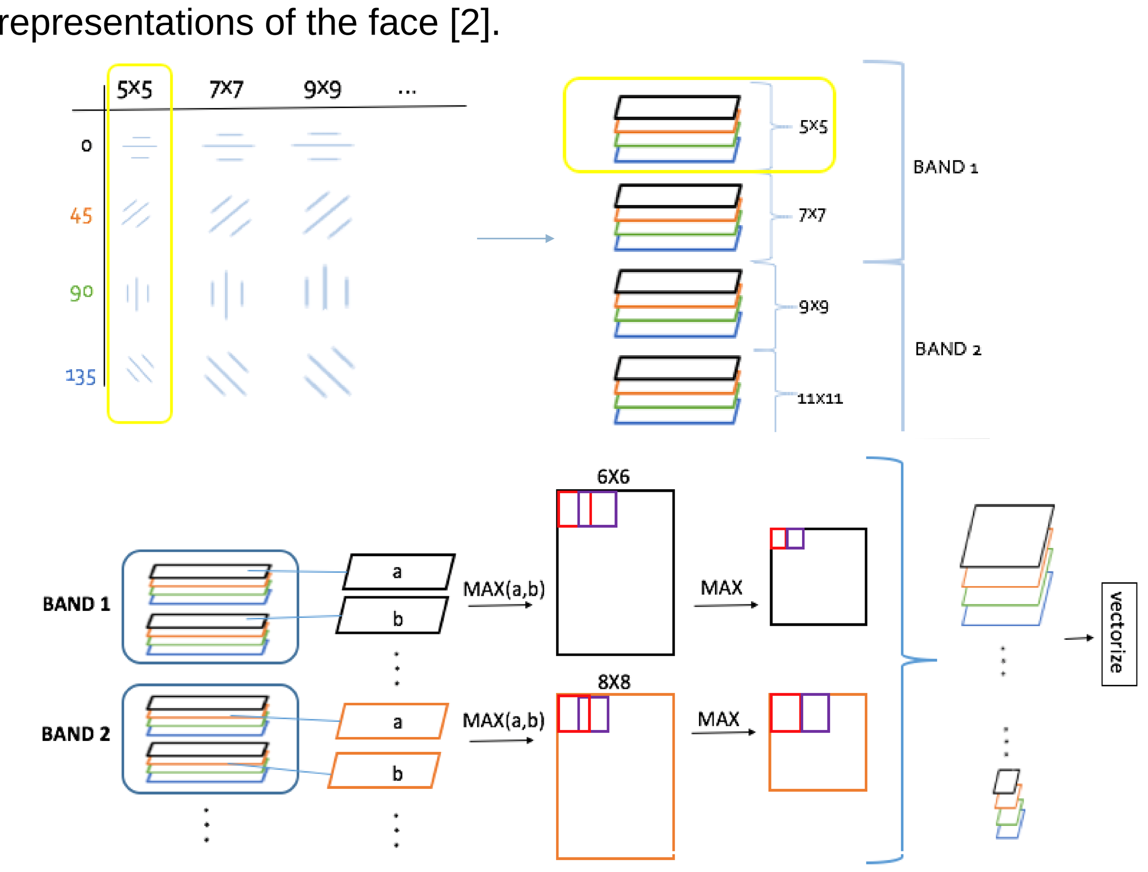


$$g(x, y; \lambda, \theta, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \cos\left(2\pi \frac{x'}{\lambda}\right)$$

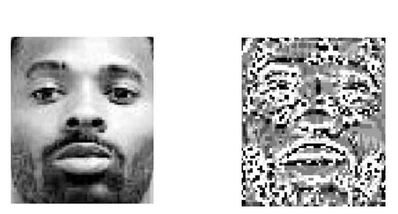
$$x' = x\cos\theta + y\sin\theta$$

$$y' = -x\sin\theta + y\cos\theta$$

**BIO-INSPIRED FEATURES:** This is a technique that emulates how the human visual system represents visual data. These features use different layers, S1 and C1, that are low-level and high-level representations of the face [2].




**LOCAL BINARY PATTERNS:** LBP feature vector is obtained by dividing the image into cells and comparing the center pixel in each cell to its neighboring pixels. Histograms are computed over each cell and then concatenated into a feature vector.

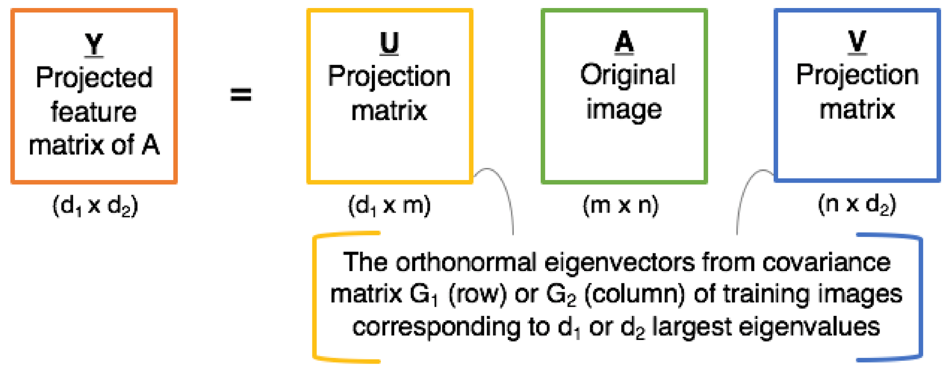


## COMPLETE 2DPCA

PCA is a classic data representation technique where the 2D image matrix is transformed into 1D image vectors. This results in a high dimensional vector space where it is difficult to calculate the covariance matrix accurately due to size [3], [4].

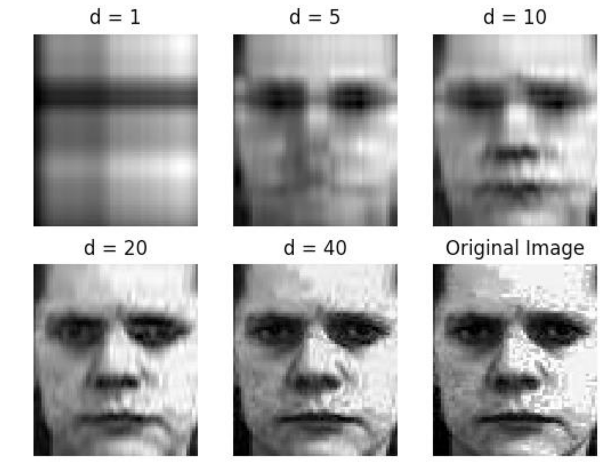
2DPCA is based on the 2D image matrices and the covariance matrix can be constructed directly from image pixels. However, 2DPCA can only reduce dimension on one side.

Complete 2DPCA uses two transformation matrices and can reduce an *m x n* image to a $d_1$ x $d_2$ feature matrix directly. As shown below:




$$G_1 = \frac{1}{M}\sum_{j=1}^{M}(\mathbf{A}_j - \bar{\mathbf{A}})(\mathbf{A}_j - \bar{\mathbf{A}})^T$$

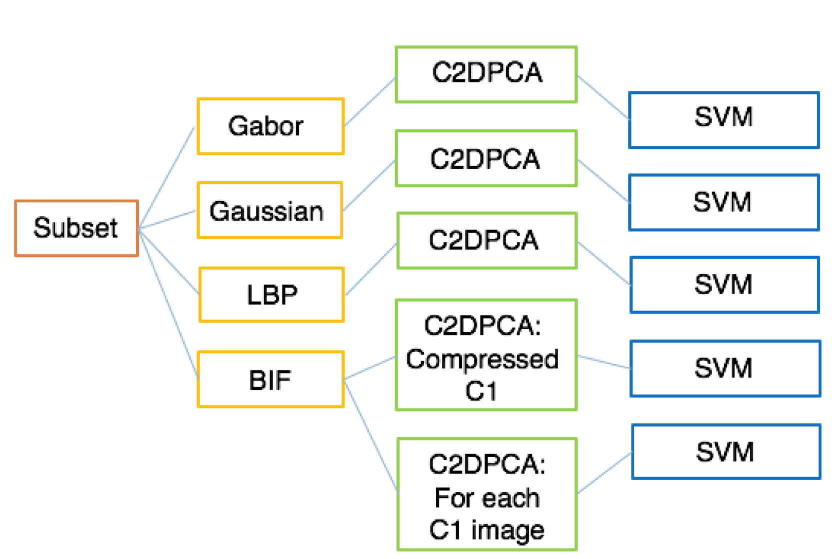
$$G_2 = \frac{1}{M}\sum_{j=1}^{M}(\mathbf{A}_j - \bar{\mathbf{A}})^T(\mathbf{A}_j - \bar{\mathbf{A}})$$




The images above represent image reconstruction with different eigenvalues in the vertical direction. For gender classification, the projected feature matrix, **Y**, is flattened into a 1D vector.

## EXPERIMENT

Experiment was set up to see which technique performed best when paired with Complete 2DPCA. It began with a subset of MORPH-II containing 1,000 images of unique subjects that maintained the black to white ratio 1:1, the male to female ratio 3:1, and a uniform age distribution of ages 21 - 45. Subsetting again resulted in 700 training and 300 testing images.




## RESULTS

Below are tables and graph representing classification accuracies for gender and computational efficiency on the subset of 1,000 images.

| | Accuracy (%) |
|---|---|
| Original | **91.7** |
| LBP | 72.7 |
| Gabor | 86.3 |
| Gaussian | 91.2 |
| BIF: Compressed | 90.7 |
| BIF: Each C1 | 90.3 |

| | Seconds |
|---|---|
| Original | 131.22 |
| LBP | 167.86 |
| Gabor | **130.84** |
| Gaussian | 150.69 |
| BIF: Compressed | 307.48 |
| BIF: Each C1 | 380.67 |

## CONCLUSIONS

From the feature extraction techniques chosen, complete 2DPCA could not be optimized further. The original image gave the highest accuracy rate. However, Gaussian and BIF weren't far behind with a < 2% difference.

Complete 2DPCA performed best because it uses the row and column information from the original image. Feature extraction techniques lose information which could be a reason those images had lower classification rates.

The Gabor Filtered images gave the worst recognition rate. Which was interesting because one paper had accuracy rates in the high 90's when paired with Complete 2DPCA on datasets of face images.

## REFERENCES


[1] K. Ricanek and T. Tesafaye. Morph: a longitudinal image database of normal adult age-progression. *In 7th International Conference on Automatic Face and Gesture Recognition (FGR06), pages 341-345, April 2006.*

[2] Ethan Meyers and Lior Wolf. Using Biologically Inspired Features for Face Processing. *International Journal Computer Vision (76): 93-104, 2008.*

[3] Anbang Xu, Xin Jin, Yugang Jiang, and Ping Guo. Complete Two-Dimensional PCA for Face Recognition. *Image Processing & Pattern Recognition Laboratory, Beijing Normal University, 2006.*

[4] Jian Yang, David Zhang, Alejandro Frangi, and Jing-Yu Yang. Two-Dimensional PCA: A New Approach to Appearance-Based Face Representation and Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 26(1): 131-137, 2004.*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