Principal Component Analysis of Natural Images

Yashila Ramesh
ECE 3803 Fall 2025
Georgia-Tech Europe

Metz, France

yramesh6@gatech.edu

***Abstract*—This project aims to introduce one of the integral components of unsupervised learning algorithms, principal component analysis.**

I. Introduction to Unsupervised Learning and Principal Component Analysis

Unsupervised learning is about discovering structure in data without labels—patterns that are "there" purely because of how the data varies. In images, that usually means learning the dominant regularities across local patches: smooth intensity changes, edges, textures, and repeats. The promise is twofold. First, you get compact representations that keep most of the information while dropping redundancy, which is useful for compression. Second, you get human-interpretable features that often line up with visual intuition—filters that look like blurs, edge detectors, and small texture templates.

Principal component analysis is the most direct way to do that. First, center your data by subtracting the global mean, then estimate the covariance of your patch matrix, and find its top eigenvectors. Those eigenvectors are the principal components—orthonormal directions that capture the most variance, ranked by their eigenvalues. Sanger in his 1989 paper [1] shows that a network trained with his generalized Hebbian algorithm, converges to this solution—the rows of the learned weight matrix become the first eigenvectors, ordered by decreasing eigenvalue—so the outputs are **uncorrelated** and ranked by explained variance. In this report, I follow these ideas by Sanger to perform a principal component analysis on a set of images.

II. Methods And Results

A. Simulation Setup

To begin the setup for this project, I used a public dataset of 1254 1200x800 images which I then cut down to 345 images. The first dataset can be found here. The second dataset can be found here. I initially used this dataset to start as I could not find a good higher quality dataset. However, later on, I found a dataset with image qualities of 1356x2040 and used a set of 345 of these images. In this report I have included the results of both datasets. Once I acquired the datasets, I began to start processing the image. To do this, I greyscaled and split each image into a set of receptive fields. For the purposes of this project. I used 8x8 blocks and 20x20 blocks for my images of 1200x800, and blocks of 6x6 and 12x12 for my images of size 1356x2040. After splitting images into receptive fields, I flattened each block into vectors that then created the matrix of inputs X . I found the covariance of the inputs and then found the eigenvalues and vectors of the matrix and performed an eigendecomposition, sorting the eigenpairs by descending eigenvalue.

B. Principal Componenets

For visualization of the principal components I reshaped the top eigenvectors back into 8x8 and 20x20 grids and visualized them as receptive-field "filters", which reveal the following edges, gradients and center-surround patterns. For the first data set:

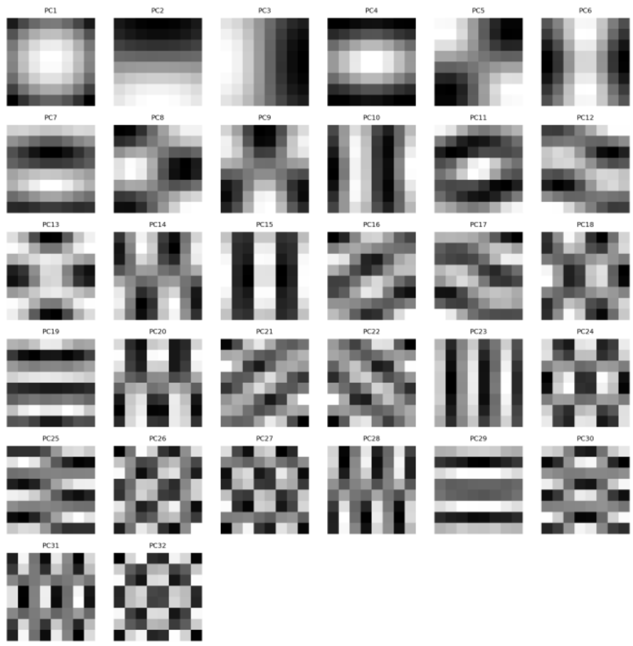


Figure 2.1: The first dataset's top 32 PCA with block size 8

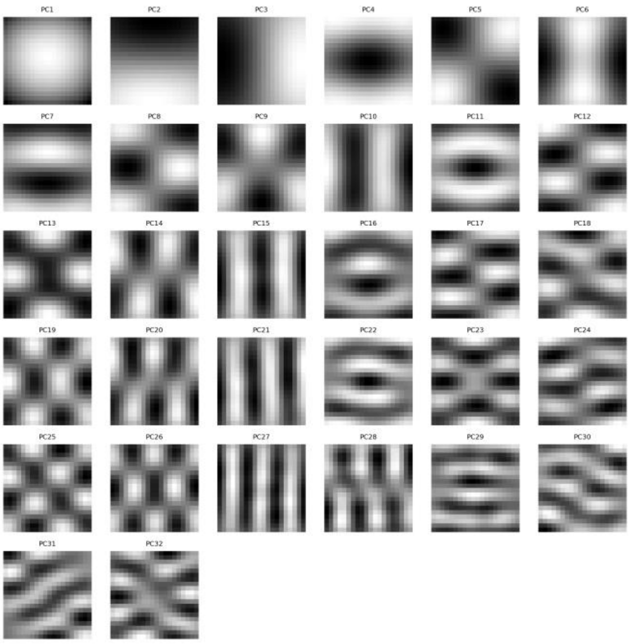


Figure 2.2: The first dataset's top 32 PCA with block size 20

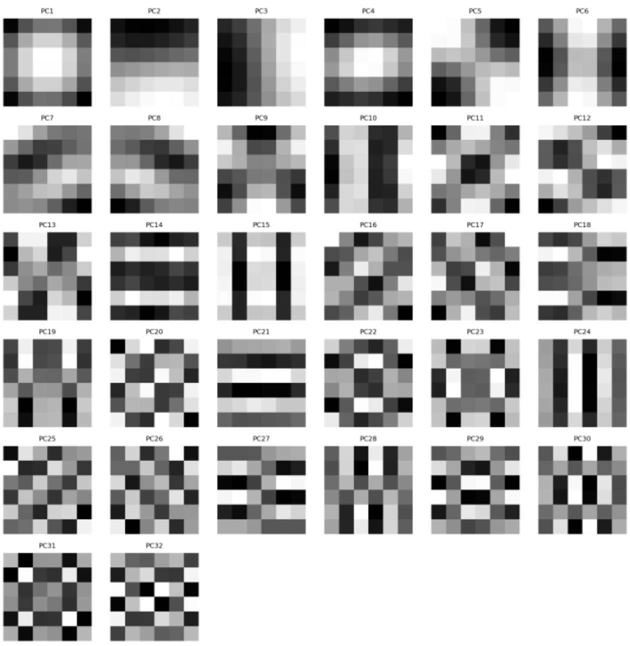


Figure 2.3: The second dataset with blocks size 6.

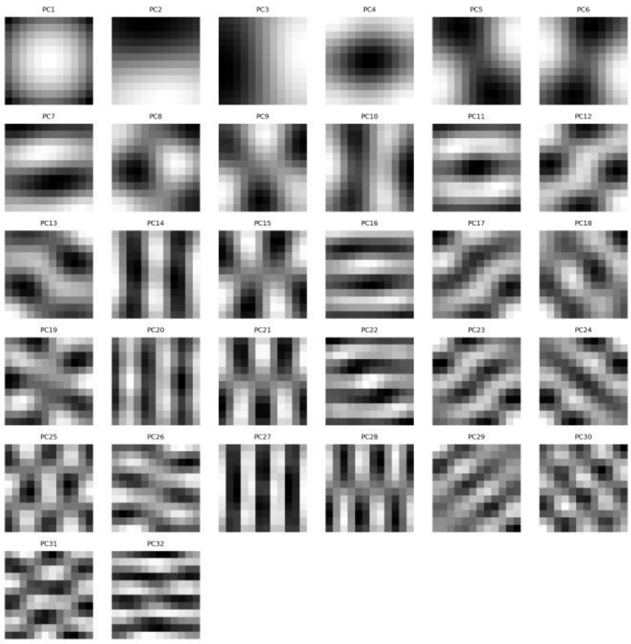


Figure 2.4: The second dataset with blocks size 12.

As can be seen from these figures. The two datasets, both sets of natural images, converge to virtually the same set of principal components. This isn't unexpected. A look into the literature reveals that it is expected for sets of natural images to converge to the same set of principal components. Pictured is a 1996 study from the University of Stirling finding the principal components of just a set of 40 images. Here are the first 15 principal components of that study.

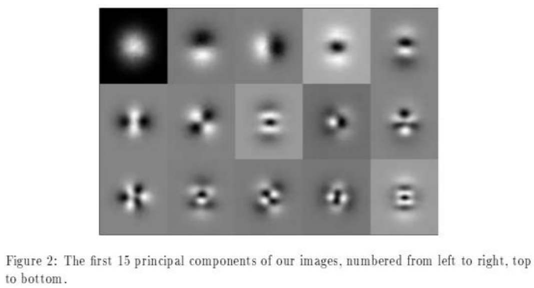


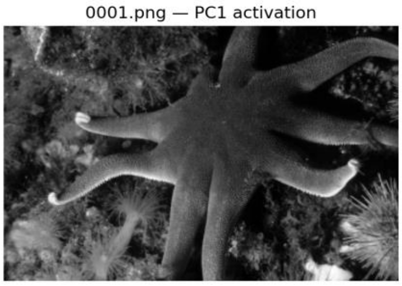
Figure 2.5: University of Stirling PCA plot [2]

It can be seen that these principal components have a very similar shape and ranking as the ones generated by my set of images. There are some slight differences between the trials, which can be attributed to the different block sizes and different image sets.

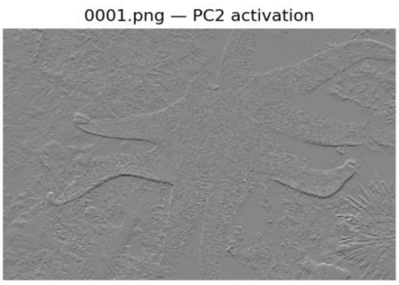
C. *Activation Map*

It is clearly of interest to see how these features translate are represented by the images. Here I projected each centered receptive field patch onto a chosen principal component by taking the dot product with that PC—and then placing each score back onto its original patch location on a non-overlapping grid. Here we can see the results with the first PC. Here is the original image:

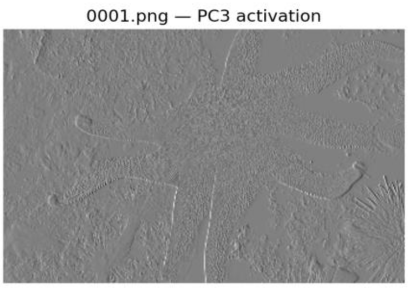
Here the image with the first PCA activated can be seen:



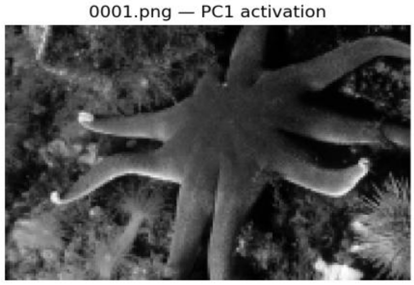
Here the image with the second PCA activated can be seen:

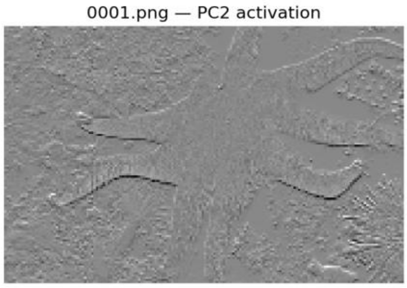


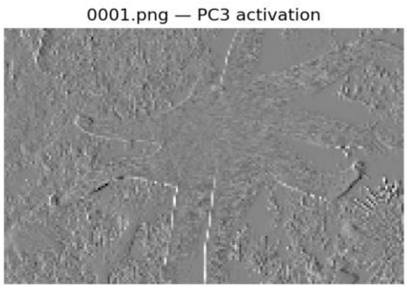
And with the Third:



These are for block size 6x6 and the following images are for block size 12x12:



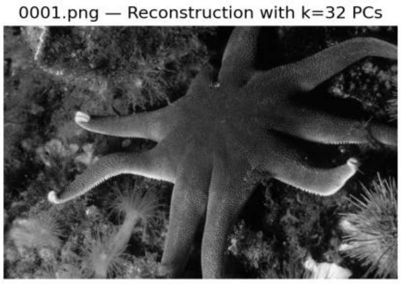


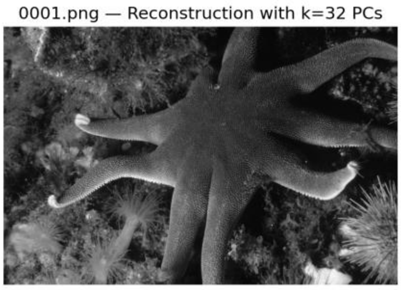


These activation maps of the principal components reveal some pretty interesting insights about the principal components themselves. It seems like the first principal component carries most of the detail and the following components carry the smaller details that accentuate the details of the photo. This makes sense as PCA ranks directions by variance. In natural photos the biggest variance is low frequency contrast. So PC1 is a low frequency/averaging filter. Where PC2/PC3 typically act like edge/gradient detectors. Their maps look like embossed/high-pass images.

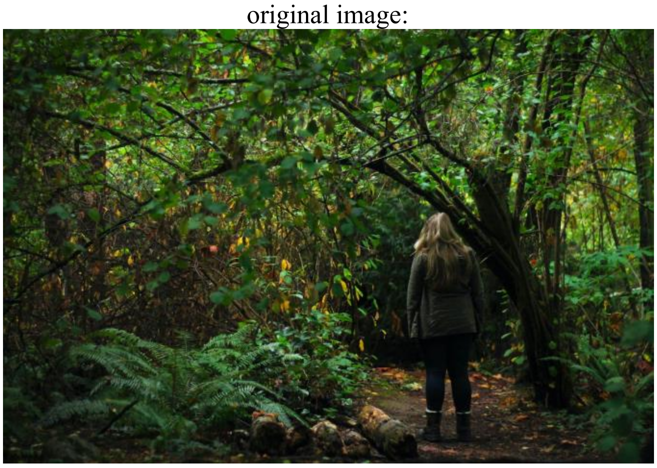
D. Reconstruction

To evaluate how well the PCA subspace captures local structure, I reconstructed each image by taking all of its non-overlapping patches, projecting the centered patch matrix onto the top k principal components, and mapping back into the pixels. Then I reshaped each reconstructed patch to its block size and tiled them back onto the original patch grid to form the full image. Here is what the reconstructions look like:





While it may be hard to tell on the pdf the smaller the block size is the better quality the reconstruction is. Interestingly here is a photo that was reconstructed twice. Here is the original image:



Reconstruction with a block size of 20x20:

And a reconstruction of the reconstruction with a block size of 20:

The reconstruction of the reconstruction shows us the compression power of PCA.

III. Conclusion

This project was a great success in my opinion and really helped me to see the theory behind PCA come to life with these tests. I felt that the process was easy to connect with the class content and strengthened my ability to turn theory to code. I found the entire process extremely rewarding and fulfilling as I was able to see each principal component come to life through the activation map and the compression potential using the reconstructions.

The results fell in line with what I expected. The principal components seem to align with other studies on the principal components of natural images and the block sizes followed the expected behavior for the principal components.

In the future if I were to do this project again. I would want to expand upon the type of algorithm used. This project focused solely PCA (Sanger) but in the future I would like to extend the methods performed here on an ICA (Bell) algorithm.

IV. References

[1] T. Sanger, "Optimal Unsupervised Learning in a Single-Layer Linear Feedforward Neural Network" in Neural Networks, vol. II, October 1988. pp. 459-473.

[2] P. JB Hancock, R. J Baddeley and L. Samuel Smith, "The Principal Components of Natural Images" in Network Computation in Neural Systems, 1970