# Facial Recognition using Eigenfaces

California State University, Long Beach
Department of Mathematics and Statistics

Noel Eom
Daan I Leiva
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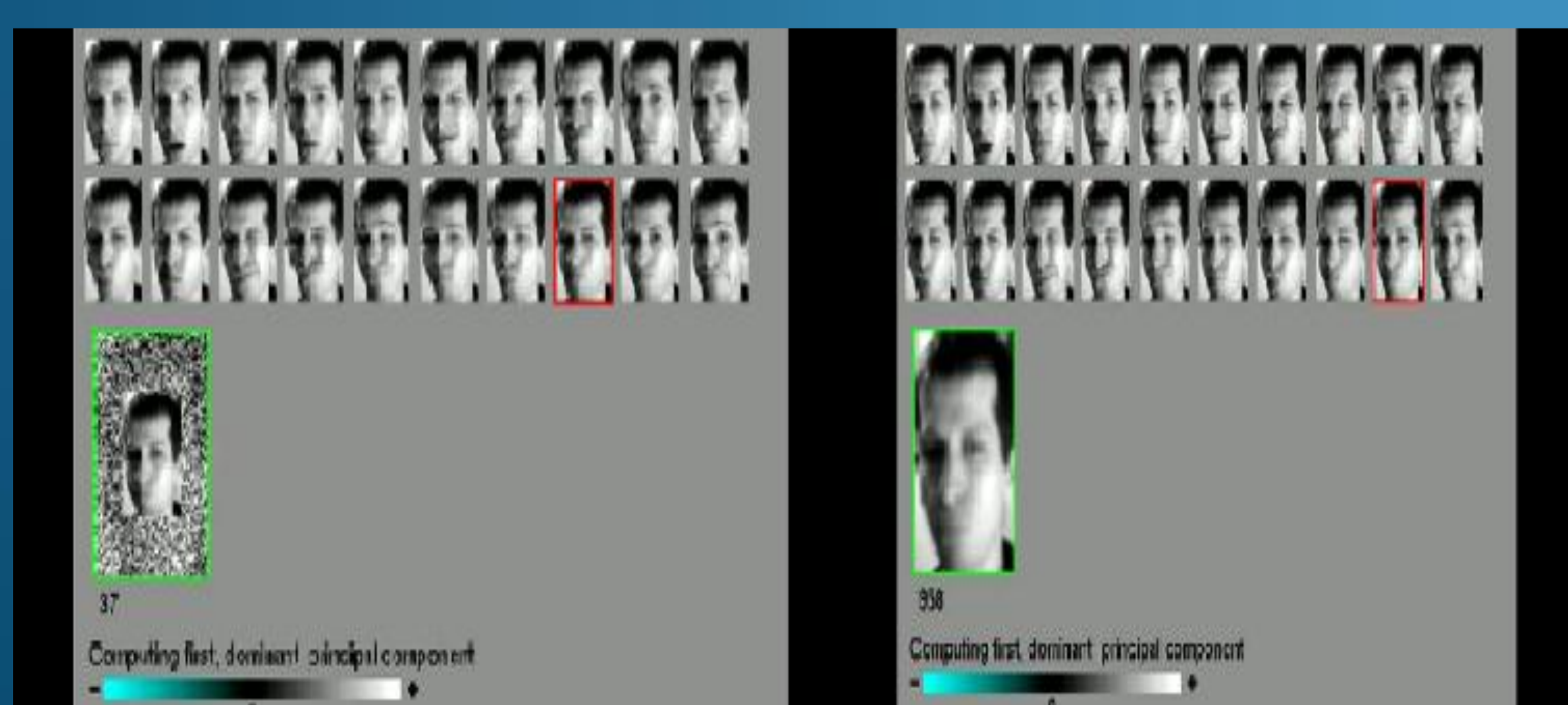
## Introduction

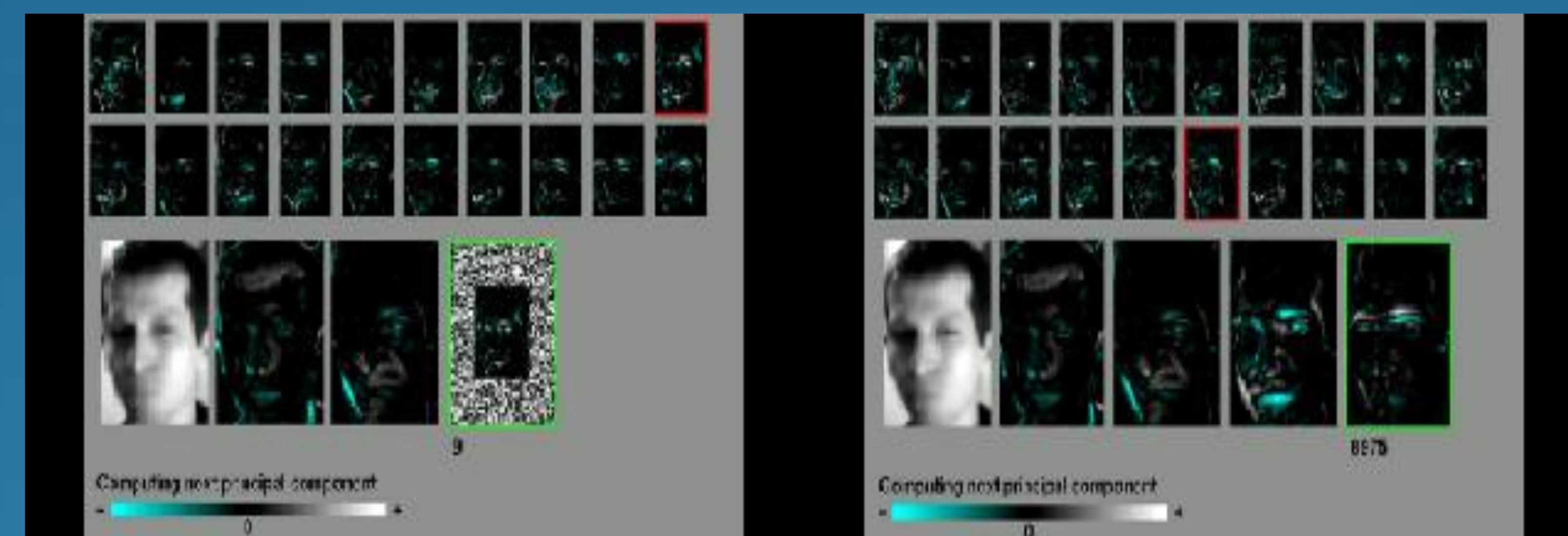
The Principal Component Analysis (PCA) Algorithm can generate a set of Eigenfaces that can be used for facial recognition methods. The goal PCA is to reduce a complex data set to a lower dimension by getting rid of unnecessary values caused by noise, rotation and redundancy. In essence it strips down a set of variables into a basic structure that can best account for the data.
The reason why facial recognition using Eigenfaces is so important is that it allows for a more efficient and less time consuming method of recognition, compared to other biometric techniques such as finger print scanning and iris recognition as well as allowing for a greater set of variables to be analyzed which is very useful in the large and constantly active society we live in.

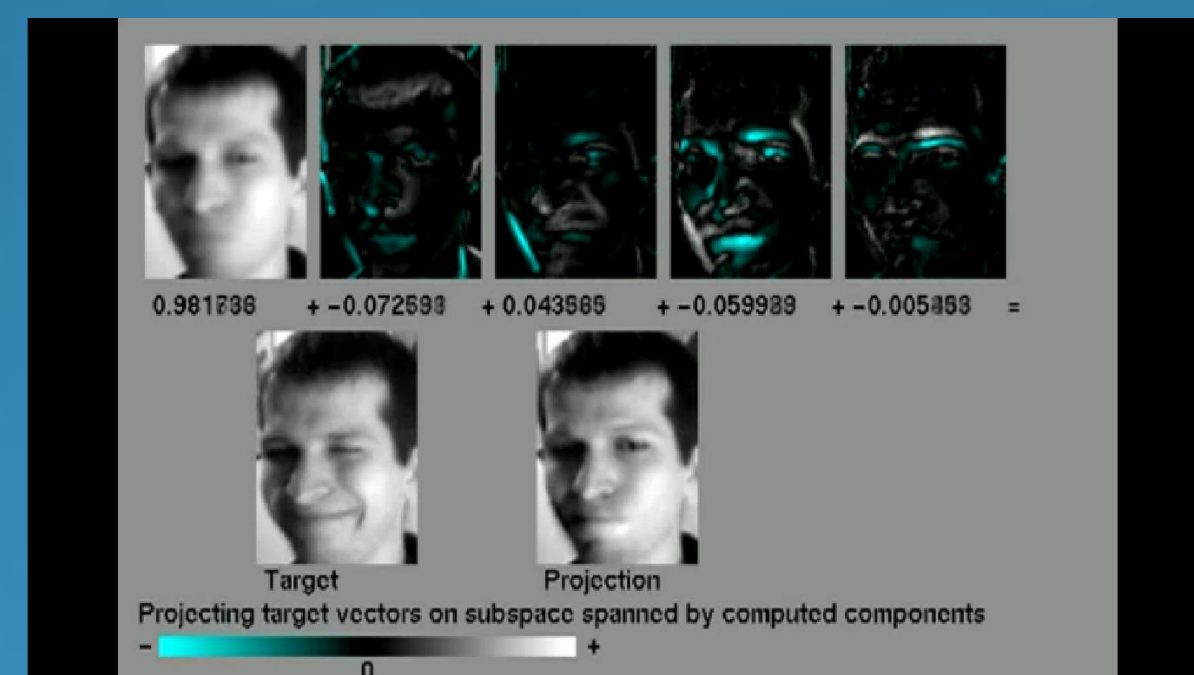
## Background

The Principal Component Analysis was created by Karl Pearson in 1901. The usage of Eigen faces for recognition was established by Sivorich and Kirby in 1987. Face Recognition techniques using Eigenfaces are now used in surveillance and security techniques. These method is used outside of face recognition as well as it is the case of handwriting analysis, lip reading, voice recognition, sign language and medical imaging (in this case they are more commonly called "Eigenimages").

## The method of Eigen faces being used for recognition graphically:








**The method conceptually:**

- You need to have a set of training faces, with mouth and eyes aligned under the same lighting.
- Using the images' pixels as vectors (and concatenating their rows) we create a matrix **S** with **M** vectors (each is image).
- We now want to find a mean image **Ψ.** We will do this by adding all our images and dividing by the number of images M.

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n$$

- Now we will find the difference Φ between our input image sand the mean image.

$$\Phi_i = \Gamma_i - \Psi$$

- Now we need to find a set of M orthonormal vectors that can describe most accurately the distribution of the data, these are eigenvectors of the covariance matrix **C.**

$$\lambda_k = \frac{1}{M}\sum_{n=1}^{M}\left(u_k^T\Phi_n\right)^2$$

- Now we want to find our covariance matrix C.

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T = AA^T$$

- The covariance helps us measure the amount of linear relation ship between the variables.
- It will also helps us capture the noise and redundancy within our vectors by showing us the correlation between pairs of values.
- We can create the Eigenfaces from these vectors using the same technique with pixels that we used at the beginning. Except because now we have orthonormal vectors which will create images that are just made of light and dark pixels' zeroes and ones ( black and white for example).
- The **recognition part.**
- We will start by finding the difference with our mean and then multiplying it times each of our Eigen vectors $u_k$. This will create weights which we will put together under a common vector Ω. You will do this for the all the eigenvectors in all of your images.
- Once you do so you can find the shortest residual by finding the residual or the closes t points between your Ωk
- You can set a values over which you will consider your image as an unknown.
- Mathematically speaking:

$$\omega_k = u_k^T(\Gamma - \Psi)$$

$$\Omega^T = [\omega_1, \omega_2, \ldots\ldots, \omega_M]$$

$$\varepsilon_k = \left\|\Omega - \Omega_k\right\|^2$$

**Results**:
After our computations we were able to determine whether the input we were looking at was a known or unknown face.

**Conclusion**:
Face recognitoin using Principal Component Analysis is only possible thanks of Eigen values due to the need of finding an orthonormal basis.
This research poster has helped me understand that linear algebra has dynamic useful everyday applications such is the case in face recognition using Eigen faces and PCA.

**Acknowledgments and References**

- Jonathon Shlens. A tutorial on Principal Component Analysis. http://www.brainmapping.org/NITP/PNA/Readings/pca.p
- Drexel University. Eigenface Tutorial. http://www.pages.drexel.edu/~sis26/Eigenface%20Tutorial.htm/