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| **SVM Project and Gender Classification** |
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| **Programming Assignment 4** |
| **Computer Science 679 – Pattern Recognition, UNR, Dr. Bebis** |
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# Abstract

This paper describes our research regarding the fourth 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, theory of support vector machines, theory of kernel functions, and classifier results. The paper also compares SVM with Bayes classifier.

# 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, again where K<N, dimensional space is defined as

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

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

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

## Support Vector Machines

Primary two-class classifier extendable to multiple-class

Performs structural risk minimization

Optimization criterion is the margin of separation

Training is equivalent to solving a quadratic programming problems with linear constraints

### Linear Decision Boundary

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

### Non-Linear mapping to Linear Decision Boundary

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

## Support Vector Machines

## Kernel Functions

# Project

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

## Experiment 1: SVM

### 16x20 Images

#### Polynomial Kernels

#### RBF Kernels

### 48x60 Images

#### Polynomial Kernels

#### RBF Kernels

## Experiment 2: Bayesian

### Training Parameters

### Testing on 16x20 Images

### Testing on 48x60 Images

## Experimental Results for High Resolution Imagery

### Training a.I: High resolution

### Testing a.II to a.IV: High resolution with 80% information

### Testing a.II to a.IV: High resolution with 90 % information

### Testing a.II to a.IV: High resolution with 95 % information

### Part b: Feature and ROC performance charts

## Experimental Results for Low Resolution Imagery

### Training a.I: Low resolution

### Testing a.II to a.IV: Low resolution with 80% information

### Testing a.II to a.IV: Low resolution with 90% information

### Testing a.II to a.IV: Low resolution with 95% information

# Conclusion

## Part A: Face recognition

## Part B: Intruder detection

# Contributors

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)