

1 Problem 1

Prove that the set of first principal components has maximum variance among any other set of principal components.

Consider a data set $X = \{x^{(\mu)} \mid \mu \in [1, P]\}$ in an N dimensional feature space. Let $C = XX^T$ be the covariance of X , and $\phi^{(i)}$ the eigenvectors of the linear equation $C\phi^{(i)} = \lambda_i\phi^{(i)}$ with eigenvalues λ_i for $i \in [1, N]$. Furthermore, order $(\lambda_i, \phi^{(i)})$ such that for $i > k$ we have $\lambda_i < \lambda_k$. Furthermore let $a_i^{(\mu)}$ be the i -th principal component of $x^{(\mu)}$ given by $a_i^{(\mu)} = \langle x^{(\mu)}, \phi^{(i)} \rangle$.

$a_i^{(\mu)}$ is thus a projection of $x^{(\mu)}$ onto the eigenvector $\phi^{(i)}$. The variance of a_i is thus the variance of X with respect to the i -th eigenvector. Since the eigenvectors $\{\phi^{(i)}\}$ are of the covariance of X , the covariance of X with respect to any $\phi^{(i)}$ is a diagonal matrix and is equal to the variance of X with respect to the same eigenvector. Therefore, $\text{Var}(a_i) = \text{Cov}(X)_{\phi^{(i)}} = \lambda_i$. By hypothesis, $\lambda_1 > \lambda_i \forall i > 1$. Therefore $\text{Var}(a_1)$ is maximal along the first principal component.

Heuristically, the first principal component is constructed to be the component along which the covariance of X is maximal. Therefore, the projection of the data set X onto the different components, which is denoted by a_i , has maximal variance along the first principal component, since the variance of X along the component is equal to the covariance with respect to that component.

2 Problem 2

Calculate and display eigenfaces as well as approximation faces.

Using the script below and `eigenface.py`, I performed PCA on the set of faces supplied. Figure 1 shows the average face, and Figure 2 show the first eight eigenfaces (in order) determined from the data set. Figure 3 shows the first face given in the set, and Figure 4 shows the first eight approximation eigenfaces.

problem2.py

```
1  #!/usr/local/bin/ipython
2  # Athanasios Athanassiadis March 2012
3  from eigenface import *
4
5  infolder = 'faces'
6  outfolder = 'eigenfaces'
7  outfolder2 = 'face_approx'
8
9  print 'loading faces'
10 origfaces, faces, shape = load_faces(infolder)
11 avgface = origfaces.sum(0) / origfaces.shape[0]
12
13 print 'computing eigenfaces'
14 eigfaces = eigenfaces(faces, 8)
15
16 print 'saving output'
17 imsave(os.path.join(outfolder, 'avgface.png'),
18        avgface)
19
20 for i in range(len(eigfaces)):
21     imsave(os.path.join(outfolder, 'eigenface%d.png' % i),
22            eigfaces[i].reshape(shape))
23
24
25 print 'calculating approximation faces for first face'
26 face = origfaces[0]
27
28 fapproxes = approxiface(face.flatten(), eigfaces, avgface.flatten(), 8)
29
30 print 'saving output'
31 imsave(os.path.join(outfolder2, 'original.png'),
32        face)
33
34 for i in range(len(fapproxes)):
35     imsave(os.path.join(outfolder2, 'approx%d.png' % (i+1)),
36            fapproxes[i].reshape(shape))
```



Figure 1: Average Face

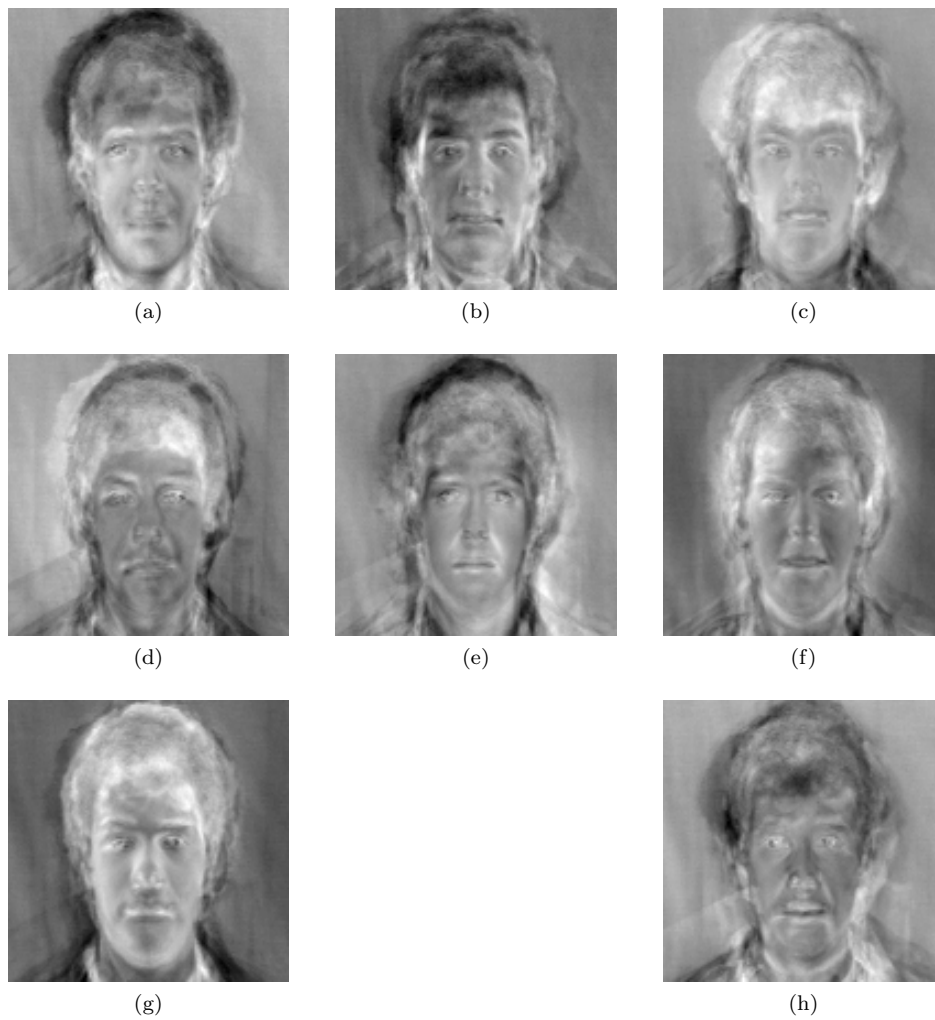


Figure 2: First 8 eigenfaces

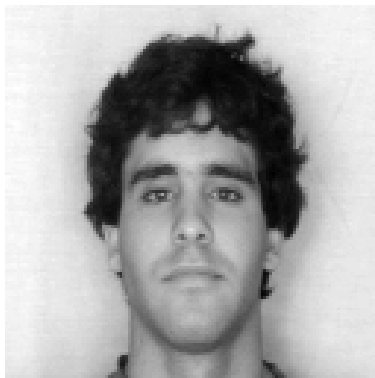


Figure 3: Input Face

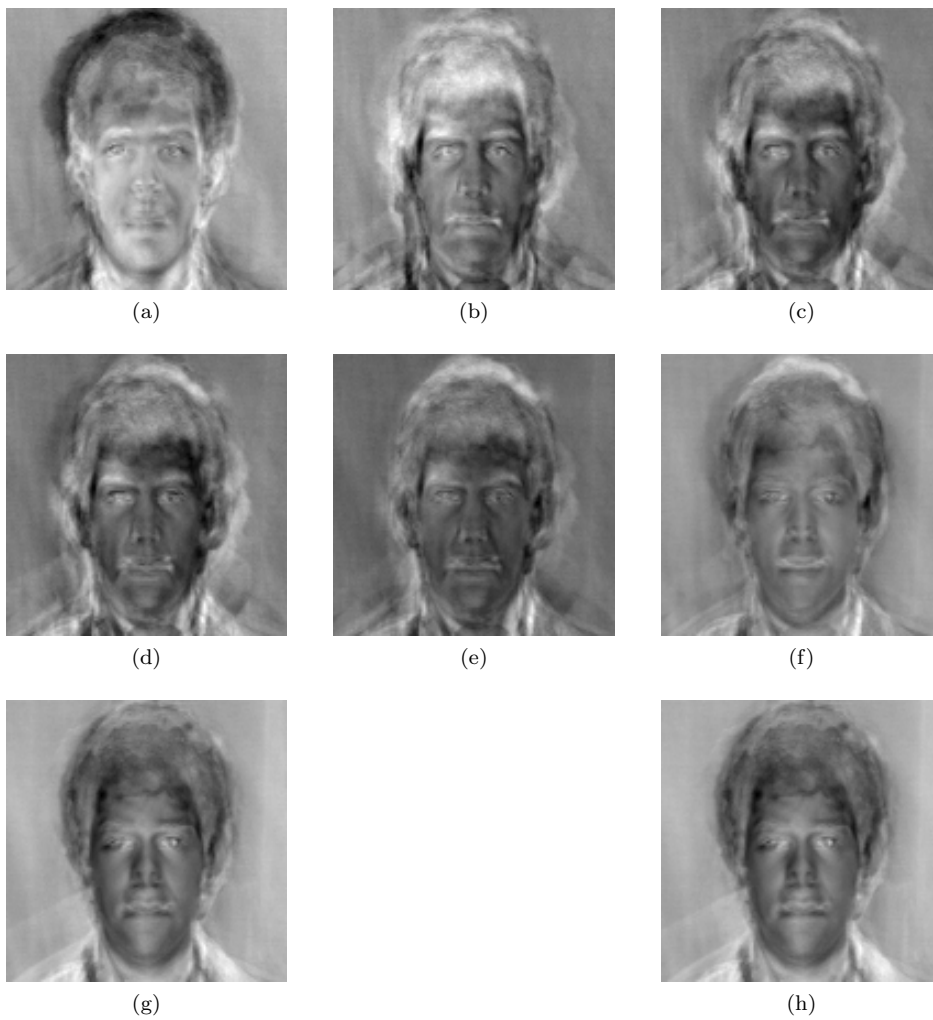


Figure 4: First 8 approximation faces

3 Appendix: Common Code

The base code used for Problem 1 in this homework is contained in `eigenface.py`.

`eigenface.py`

```
1 # Athanasios Athanassiadis March 2012
2 import os
3 import numpy as np
4 from numpy.linalg import eig
5 from scipy.misc import imread, imsave
6
7
8 cov = np.cov
9
10 def load_faces(folder):
11     """
12     load_faces
13         load a set of faces from a folder of tif images
14         and return reduced set of faces with shape info
15     """
16
17     filelist = os.listdir(folder)
18
19     origfaces = []
20     for fn in filelist:
21         origfaces.append(
22             imread(os.path.join(folder, fn)))
23
24     origfaces = np.array(origfaces).astype(np.int16)
25
26     avgface = origfaces.sum(0) / origfaces.shape[0]
27     shape = avgface.shape
28
29     # make faces to process zero-mean
30     faces = np.array([(face - avgface).flatten() for face in origfaces]).T
31
32
33     return origfaces, faces, shape
34
35 def eigenfaces(faces, n=None):
36     """
37     eigenfaces
38         returns the first n eigenfaces (principal components)
39         calculated from an array of face which has been reduced to 2D
40
41         eigenfaces are the eigenvectors of the covariance matrix of the
42         faces matrix
43
44         this computation is simplified using the Turk-Pentland Trick
45     """
46
47
48     C = cov(faces.T, bias=1)
49
50     # columns in eigvecs represent individual eigenvectors
51     # that correspond to each eigenval
```

```
52 eigvals , eigvecs = eig(C)
53
54 if n is None or n>len(eigvals):
55     n = len(eigvals)
56
57 # sort by eigenvalue (decreasing)
58 # and transpose so rows contain eigenvectors
59 eigzip = zip(eigvals , eigvecs.T)
60 eigzip.sort(key = lambda x: x[0])
61 eigvecs_sorted = np.array([pair[1] for pair in eigzip[::-1]])
62
63 eigfaces = np.zeros((n, faces.shape[0]))
64
65 # calculate eigenfaces from eigenvectors and zero-mean faces
66 # according to Turk-Pentland
67 for l in range(n):
68     for k in range(faces.shape[1]):
69         eigfaces[l] += (eigvecs[l,k] * faces[:,k])
70
71 return eigfaces.astype(np.int16)
72
73 def approxiface(face , eigfaces , avgface , n=None):
74     """
75     approxiface
76     approximate a face b,ased on eigfaces
77     return first n approximations
78
79     """
80
81     if n is None or n>len(eigfaces):
82         n = len(eigfaces)
83
84     weights = np.zeros(n)
85
86     # calculate projection on to each axis (eigenface)
87     for k in range(n):
88         weights[k] = np.dot(eigfaces[k] , face-avgface)
89
90     # normalize so that norm(weights) = 1
91     weights /= np.sqrt((weights**2).sum())
92
93     # calculate first n approximation faces
94     approxes = np.zeros((n, eigfaces.shape[1]))
95     approxes[0] = weights[0] * eigfaces[0]
96     for k in range(1,n):
97         approxes[k] = approxes[k-1] + (weights[k] * eigfaces[k])
98
99     return approxes
```