(EC5, analytical) Consider  $\mathbf{A} \in \mathbb{R}^{m \times m}$ ,  $\mathbf{A} = \mathbf{A}^T$ , for which we know that the eigenvalues are distinct and positive,  $\lambda_1 > \lambda_2 > ... > \lambda_m > 0$ ,  $\mathbf{A}\mathbf{x}_j = \lambda_j \mathbf{x}_j$ . Consider the sequence of vectors  $\mathbf{v}_k = \mathbf{A}^k \mathbf{v}_0$ .

(1) What is  $\lim_{k\to\infty} v_k$ ?

(2) Based on the above analysis, devise a procedure to find the  $\boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3$  as limits of sequences  $\boldsymbol{v}_k = \boldsymbol{A}^k \boldsymbol{v}_0$  with appropriately chosen initial vectors  $\boldsymbol{v}_0$ .

(EC6, computational) In an experimental data acquisition process n measurements of m components are obtained, forming a matrix of observations  $\mathbf{X} = (\mathbf{x}_1 \ \dots \ \mathbf{x}_n) \in \mathbb{R}^{m \times n}$ . Each column is an observation of the m components measured experimentally. The mean of the observations is

$$\boldsymbol{\mu} = \frac{1}{n} \sum_{j=1}^{n} \boldsymbol{x}_{j} \in \mathbb{R}^{m}.$$

The deviation from the mean of observation j is

$$\boldsymbol{y}_j = \boldsymbol{x}_j - \boldsymbol{\mu},$$

from which the centered observation matrix  $\mathbf{Y} = (\mathbf{y}_1 \dots \mathbf{y}_n) \in \mathbb{R}^{m \times n}$  is formed. The sample covariance matrix is defined as

$$S = \frac{1}{n-1} Y Y^T \in \mathbb{R}^{m \times m}$$

(1) Express S in terms of the singular value decomposition of Y.

(2) Revisit the yalefaces database. Consider each facial image as an observation  $x_j$ . Display the principal components of the images, i.e., from

$$\boldsymbol{Y} = \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^T = \sum_{j=1}^r \sigma_j \boldsymbol{u}_j \boldsymbol{v}_j^T \cong \sum_{j=1}^k \sigma_j \boldsymbol{u}_j \boldsymbol{v}_j^T$$

show the images obtained for k = 1, 2, ..., 6.