

**Guidelines**

- Write your name and matriculation number on each sheet of paper.
- Only clearly readable exercise-elaborations are evaluated.
- Results have to be provided together with an evident way of calculation.
- Keep textual answers short and concise. Lengthy or vague statements won't gain points.

**Exercise 7.1 (0.5 points)**

Consider a set of Hermitian matrices  $A^{(i)}$ ,  $i = 1, \dots, N$  of dimension  $M \times M$ .

1. Show that the following matrices are also Hermitian:

(a)  $\sum_{i=1}^N A^{(i)}$

(b)  $A^{(i)} (A^{(i)})^H$

(c)  $\sum_{i=1}^N A^{(i)} (A^{(i)})^H$

2. Assume that all Hermitian matrices  $A^{(i)}$ ,  $i = 1, \dots, N$  can be diagonalized by the same unitary matrix  $Q$ . Determine tight upper and lower bounds of  $\sum_{i=1}^N \frac{\underline{x}^H A^{(i)} \underline{x}}{\underline{x}^H \underline{x}}$  in terms of eigenvalues of the matrices  $A^{(i)}$ .

3. Show that  $\sum_{i=1}^N \left( \frac{\underline{x}^H A^{(i)} \underline{x}}{\underline{x}^H \underline{x}} \right)^2$  is bounded by

$$\frac{1}{N} \left( \frac{\underline{x}^H \sum_{i=1}^N A^{(i)} \underline{x}}{\underline{x}^H \underline{x}} \right)^2 \leq \sum_{i=1}^N \left( \frac{\underline{x}^H A^{(i)} \underline{x}}{\underline{x}^H \underline{x}} \right)^2 \leq \sum_{i=1}^N \frac{\underline{x}^H A^{(i)} A^{(i),H} \underline{x}}{\underline{x}^H \underline{x}}, \quad (1)$$

where  $\underline{x}$  is an arbitrary non-zero vector.

(Hint: use Cauchy-Schwarz.)

**Exercise 7.2 (0.5 points)**

Consider a square matrix  $Q$  with  $\|Q\| < 1$  and the norm  $\|\cdot\|$  satisfies the submultiplicative property

1. Proof the following inequality:

$$\|(I - Q)^{-1}\| \leq \frac{1}{1 - \|Q\|}$$

(Hint: Use the Neumann expansion (Theorem 4.2))

2. Furthermore show

$$\|I - (I - Q)^{-1}\| \leq \frac{\|Q\|}{1 - \|Q\|}$$

(Hint: Show that  $I - (I - Q)^{-1} = -Q(I - Q)^{-1}$ )

Now assume  $A$  to be nonsingular and  $E$  such that  $\|A^{-1}E\| < 1$ .

3. Show that  $A + E$  is nonsingular. (Hint: utilize previous results)
4. Let  $Q = -A^{-1}E$ . Show that  $Q$  satisfies:

$$(A + E)^{-1} = (I - Q)^{-1}A^{-1}$$

5. Show that  $(A + E)^{-1} - A^{-1} = -A^{-1}E(A + E)^{-1}$
6. Finally, show that:

$$\|(A + E)^{-1} - A^{-1}\| \leq \frac{\|A^{-1}\|^2\|E\|}{1 - \|Q\|} \quad (2)$$

**Exercise 7.3 (0.75 points)**

Consider the iterative algorithm introduced in Example 4.24 in the lecture notes. In this exercise, we apply the algorithm for calculating the inverse  $R^{-1}$  of a Hermitian matrix  $R = AA^H$  of dimension  $N_R \times N_R$ .

1. Consider the modified algorithm

$$W_{k+1} = W_k + \mu_k W_k (I - RW_k^H W_k) \quad (3)$$

with bounded step size

$$0 < \mu_k < \frac{2}{\sigma_k^{(max)} [1 + \sigma_k^{(max)}]}, \quad (4)$$

where  $\sigma_k^{(max)}$  denotes the maximum singular value of  $W_k A$ . Assume that the Singular Value Decomposition (SVD) of  $W_k A$  is  $W_k A = U \Sigma_k V^H$ .

Your task is to analytically show that the modified algorithm as given in Equation (3) converges towards  $W_\infty^H W_\infty = R^{-1} = (AA^H)^{-1}$ .

(Hint: multiply Equation (3) with  $A$  from the right and show that the singular values in  $\Sigma_k$  converge towards 1, given Equation (4) is satisfied. Use this results to proof the convergence of  $W_\infty^H W_\infty$ .)

2. Write a MATLAB program which performs the iterative algorithm to compute the inverse. Use the relative Mean Squared Error (MSE)

$$MSE_k = \frac{1}{N_R^2} \|RW_k^H W_k - I\|_F^2 \quad (5)$$

to show the convergence. Your output should be a plot of MSE versus the iteration step. For the step size calculation, use the relation

$$0 < \frac{2}{0.25 + 2\lambda_k^{(max)}} < \frac{2}{\sigma_k^{(max)} [1 + \sigma_k^{(max)}]}, \quad (6)$$

where  $\lambda_k^{(max)} = (\sigma_k^{(max)})^2$  denotes the maximum eigenvalue of  $W_k RW_k^H$ . Generate a suitable matrix for inversion (of dimension  $N_R = 5$ ) by using the `randn` command in MATLAB. Set  $W_0 = I$ .

**MATLAB-Exercise 7.1 (1.25 points)**

Consider the following signal model:

$$s_k = \sum_{i=1}^p a_p e^{j2\pi f_p k} + n_k \quad (7)$$

The signal is a superposition of  $p$  sinusoids with amplitudes  $a_p$  and frequencies  $f_p$  and it is disturbed by additive white Gaussian noise  $n_k$  of variance  $\sigma_n^2 = 0.1$ .

1. Assume  $p = 3$ ,  $f_1 = 0.1$ ,  $f_2 = 0.25$ ,  $f_3 = 0.4$  and  $a_1 = \frac{1}{\sqrt{2}}$ ,  $a_2 = \frac{1}{\sqrt{4}}$  and  $a_3 = \frac{1}{\sqrt{8}}$ . Implement the signal model in Matlab and generate 100 samples. In order to make your results reproducible, use a fixed seed to setup the random number generator of Matlab. To generate a random number stream with a fixed seed use the following code:

$$\text{stream} = \text{RandStream}('mt19937ar', 'Seed', 1); \quad (8)$$

When you generate the random noise, handover this stream to the function `randn` (the Matlab documentation of `randn` tells you how to do that).

2. From the generated noisy signal-samples, estimate the number of sinusoids  $p$  based on an estimate of the autocorrelation matrix of the signal of size  $20 \times 20$ . Do **NOT** use Matlab internal functions like `xcorr` or `cov` for that purpose. Plot (`stem`) the eigenvalues (`eig`) of the autocorrelation matrix.
3. Estimate the noise power from the appropriate eigenvalues of the autocorrelation matrix and state the estimated value.
4. Using the PHD algorithm estimate the frequencies  $f_p$  of the sinusoids. Plot your decision function and state the estimated values.
5. Using the MUSIC algorithm estimate the frequencies  $f_p$  of the sinusoids. Plot your decision function and state the estimated values.
6. Repeat the same steps for a signal length of 1000 samples.