

P4.12. Given the original canonical form of the performance surface

$$\xi = \xi_{min} + \mathbf{v}^H \mathbf{R} \mathbf{v}$$

$\mathbf{v} = \mathbf{w} - \mathbf{w}_o$ is the tap weight error vector, and \mathbf{R} is the autocorrelation matrix which can be written in its diagonalized form

$$\begin{aligned} \xi &= \xi_{min} + \mathbf{v}^H \mathbf{Q} \mathbf{\Lambda} \mathbf{Q}^H \mathbf{v} \\ &= \xi_{min} + (\mathbf{Q}^H \mathbf{v})^H \mathbf{\Lambda} (\mathbf{Q}^H \mathbf{v}) \\ &= \xi_{min} + \mathbf{v}^H \mathbf{\Lambda} \mathbf{v}' \end{aligned}$$

P4.13. (i)

$$x(n) = a_1 e^{j\omega_1 n} + a_2 e^{j\omega_2 n} + v(n)$$

$$x(n)x^*(n-k) = (a_1 e^{j\omega_1 n} + a_2 e^{j\omega_2 n} + v(n))(a_1^* e^{-j\omega_1(n-k)} + a_2^* e^{-j\omega_2(n-k)} + v^*(n-k))$$

Taking the expectation gives

$$\begin{aligned} E[x(n)x^*(n-k)] &= E[v(n)v^*(n-k)] + E[a_1 a_1^* e^{j\omega_1 k}] + E[a_2 a_2^* e^{j\omega_2 k}] \\ &= \sigma_v^2 \delta(k) + \sigma_1^2 e^{j\omega_1 k} + \sigma_2^2 e^{j\omega_2 k} \end{aligned}$$

as the expectation of all cross terms will be equal to zero. We can write this in matrix form as

$$\mathbf{R} = \sigma_v^2 \mathbf{I} + \sigma_1^2 \mathbf{R}_1 + \sigma_2^2 \mathbf{R}_2 \quad (1)$$

where

$$\mathbf{R}_i = \begin{bmatrix} 1 & e^{j\omega_i} & e^{j2\omega_i} & \dots & e^{j(N-1)\omega_i} \\ e^{-j\omega_i} & 1 & e^{j\omega_i} & \dots & e^{j(N-2)\omega_i} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ e^{-j(N-1)\omega_i} & e^{-j(N-2)\omega_i} & e^{-j(N-3)\omega_i} & \dots & 1 \end{bmatrix}, i = 1, 2.$$

(ii) The eigenvector corresponding to the minimum eigenvalue of \mathbf{R} is obtained by finding \mathbf{q}_{N-1} which minimizes $\mathbf{q}_{N-1}^H \mathbf{R} \mathbf{q}_{N-1}$, subject to the constraint that $\mathbf{q}_{N-1}^H \mathbf{q}_{N-1} = 1$.

$$\mathbf{q}_{N-1}^H \mathbf{R} \mathbf{q}_{N-1} = \underbrace{\sigma_v^2 \mathbf{q}_{N-1}^H \mathbf{I} \mathbf{q}_{N-1}}_{=1} + \underbrace{\sigma_1^2 \mathbf{q}_{N-1}^H \mathbf{R}_1 \mathbf{q}_{N-1}}_{\geq 0} + \underbrace{\sigma_2^2 \mathbf{q}_{N-1}^H \mathbf{R}_2 \mathbf{q}_{N-1}}_{\geq 0}$$

The latter inequalities result from the positive-definiteness of \mathbf{R}_1 and \mathbf{R}_2 . Thus $\mathbf{q}_{N-1}^H \mathbf{R} \mathbf{q}_{N-1}$ will be minimized if

$$\mathbf{q}_{N-1}^H \mathbf{R}_1 \mathbf{q}_{N-1} = \mathbf{q}_{N-1}^H \mathbf{R}_2 \mathbf{q}_{N-1} = 0 \quad (2)$$

As was done in Problem P4.7, we can show that any vector orthogonal to the two eigenfilters

$$\mathbf{u}_0 = \frac{1}{\sqrt{N}} [1 \quad e^{-j\omega_1} \quad e^{-j2\omega_1} \quad \dots \quad e^{-j(N-1)\omega_1}]^T$$

and

$$\mathbf{u}_1 = \frac{1}{\sqrt{N}} [1 \quad e^{-j\omega_2} \quad e^{-j2\omega_2} \quad \dots \quad e^{-j(N-1)\omega_2}]^T$$

will satisfy (2). Furthermore, \mathbf{u}_0 and \mathbf{u}_1 span a 2-dimensional subspace in of the N -dimensional complex vector space. Therefore there are $N-2$ mutually orthonormal vectors which satisfy (2). They are all eigenvectors of $\mathbf{R} = \sigma_v^2 \mathbf{I} + \sigma_1^2 \mathbf{R}_1 + \sigma_2^2 \mathbf{R}_2$ each with eigenvalue σ_v^2 .

- (iii) Since there is an $(N-2)$ -dimensional space spanned by eigenvectors \mathbf{q}_2 to \mathbf{q}_{N-1} , each with the degenerate eigenvalue $\lambda_2 = \dots = \lambda_{N-1} = \sigma_\nu^2$, the remaining two eigenvectors must lie within the remaining 2-dimensional subspace which is spanned by \mathbf{u}_0 and \mathbf{u}_1 . We can therefore write these eigenvectors as a linear combination of \mathbf{u}_0 and \mathbf{u}_1 :

$$\mathbf{q}_0 = \alpha_{00}\mathbf{u}_0 + \alpha_{01}\mathbf{u}_1$$

and

$$\mathbf{q}_1 = \alpha_{10}\mathbf{u}_0 + \alpha_{11}\mathbf{u}_1$$

Using the minimax theorem, we may obtain the largest eigenvector \mathbf{q}_0 , or alternatively the coefficients α_{00} and α_{01} , by maximizing the quantity:

$$\begin{aligned} \max_{\|\mathbf{q}_0\|=1} \mathbf{q}_0^H \mathbf{R} \mathbf{q}_0 &= \max_{\|\mathbf{q}_0\|=1} [\mathbf{q}_0^H (\sigma_\nu^2 \mathbf{I}) \mathbf{q}_0 + \mathbf{q}_0^H (\sigma_1^2 \mathbf{R}_1) \mathbf{q}_0 + \mathbf{q}_0^H (\sigma_2^2 \mathbf{R}_2) \mathbf{q}_0] \\ &= \max_{\|\mathbf{q}_0\|=1} [\sigma_\nu^2 + \sigma_1^2 (\mathbf{q}_0^H \mathbf{R}_1 \mathbf{q}_0) + \sigma_2^2 (\mathbf{q}_0^H \mathbf{R}_2 \mathbf{q}_0)] \end{aligned} \quad (3)$$

We may similarly obtain the smaller eigenvector in this 2-dimensional subspace \mathbf{q}_1 , or alternatively the coefficients α_{10} and α_{11} by minimizing the quantity:

$$\begin{aligned} \min_{\|\mathbf{q}_1\|=1} \mathbf{q}_1^H \mathbf{R} \mathbf{q}_1 &= \min_{\|\mathbf{q}_1\|=1} [\mathbf{q}_1^H (\sigma_\nu^2 \mathbf{I}) \mathbf{q}_1 + \mathbf{q}_1^H (\sigma_1^2 \mathbf{R}_1) \mathbf{q}_1 + \mathbf{q}_1^H (\sigma_2^2 \mathbf{R}_2) \mathbf{q}_1] \\ &= \min_{\|\mathbf{q}_1\|=1} [\sigma_\nu^2 + \sigma_1^2 (\mathbf{q}_1^H \mathbf{R}_1 \mathbf{q}_1) + \sigma_2^2 (\mathbf{q}_1^H \mathbf{R}_2 \mathbf{q}_1)] \end{aligned} \quad (4)$$

Similar to Problem P4.7, noting that

$$\mathbf{R}_1 = \sqrt{N} \begin{bmatrix} \mathbf{u}_0^H \\ e^{-j\omega_1} \mathbf{u}_0^H \\ \vdots \\ e^{-j\omega_1(N-1)} \mathbf{u}_0^H \end{bmatrix} \quad \text{and} \quad \mathbf{R}_2 = \sqrt{N} \begin{bmatrix} \mathbf{u}_1^H \\ e^{-j\omega_2} \mathbf{u}_1^H \\ \vdots \\ e^{-j\omega_2(N-1)} \mathbf{u}_1^H \end{bmatrix},$$

we have

$$\mathbf{R}_1 \mathbf{u}_0 = N \mathbf{u}_0 \quad \text{and} \quad \mathbf{R}_2 \mathbf{u}_1 = N \mathbf{u}_1$$

Defining $\beta = \mathbf{u}_0^H \mathbf{u}_1$ we also get

$$\begin{aligned} \mathbf{R}_1 \mathbf{u}_1 &= \sqrt{N} \begin{bmatrix} \mathbf{u}_0^H \\ e^{-j\omega_1} \mathbf{u}_0^H \\ \vdots \\ e^{-j\omega_1(N-1)} \mathbf{u}_0^H \end{bmatrix} \mathbf{u}_1 = \sqrt{N} \begin{bmatrix} \beta \\ e^{-j\omega_1} \beta \\ \vdots \\ e^{-j\omega_1(N-1)} \beta \end{bmatrix} = \beta \sqrt{N} \mathbf{u}_0 \\ \mathbf{R}_2 \mathbf{u}_0 &= \sqrt{N} \begin{bmatrix} \mathbf{u}_1^H \\ e^{-j\omega_2} \mathbf{u}_1^H \\ \vdots \\ e^{-j\omega_2(N-1)} \mathbf{u}_1^H \end{bmatrix} \mathbf{u}_0 = \sqrt{N} \begin{bmatrix} \beta^* \\ e^{-j\omega_2} \beta^* \\ \vdots \\ e^{-j\omega_2(N-1)} \beta^* \end{bmatrix} = \beta^* \sqrt{N} \mathbf{u}_1 \end{aligned}$$

Using these equations, we can go about evaluating an expression for the relevant terms in (3).

$$\mathbf{R}_1 \mathbf{q}_0 = \mathbf{R}_1 (\alpha_{00} \mathbf{u}_0 + \alpha_{01} \mathbf{u}_1) = (\alpha_{00} N + \alpha_{01} \beta \sqrt{N}) \mathbf{u}_0$$

$$\mathbf{R}_2 \mathbf{q}_0 = \mathbf{R}_2 (\alpha_{00} \mathbf{u}_0 + \alpha_{01} \mathbf{u}_1) = (\alpha_{00} \beta^* \sqrt{N} + \alpha_{01} N) \mathbf{u}_1$$

giving

$$\mathbf{q}_0^H \mathbf{R}_1 \mathbf{q}_0 = (\alpha_{00} N + \alpha_{01} \beta \sqrt{N}) (\alpha_{00} \mathbf{u}_0 + \alpha_{01} \mathbf{u}_1)^H \mathbf{u}_0$$

$$= (\alpha_{00} N + \alpha_{01} \beta \sqrt{N}) (\alpha_{00}^* + \alpha_{01}^* \beta^*)$$

$$\mathbf{q}_0^H \mathbf{R}_2 \mathbf{q}_0 = (\alpha_{00} \beta^* \sqrt{N} + \alpha_{01} N) (\alpha_{00} \mathbf{u}_0 + \alpha_{01} \mathbf{u}_1)^H \mathbf{u}_1$$

$$= (\alpha_{00} \beta^* \sqrt{N} + \alpha_{01} N) (\alpha_{00}^* \beta + \alpha_{01}^*)$$

by a similar procedure, we can obtain equivalent expressions for the terms in (4).

$$\begin{aligned}\mathbf{q}_1^H \mathbf{R}_1 \mathbf{q}_1 &= (\alpha_{10} N + \alpha_{11} \beta \sqrt{N})(\alpha_{10}^* + \alpha_{11}^* \beta^*) \\ \mathbf{q}_1^H \mathbf{R}_2 \mathbf{q}_1 &= (\alpha_{10} \beta^* \sqrt{N} + \alpha_{11} N)(\alpha_{10}^* \beta + \alpha_{11}^*)\end{aligned}$$

Maximizing (3) and minimizing (4) with respect to the coefficients $\alpha_{00}, \alpha_{01}, \alpha_{10}, \alpha_{11}$ will result in the two largest eigenvectors.

(iv) When $\mathbf{u}_0^H \mathbf{u}_1 = \beta = 0$, then

$$\begin{aligned}\mathbf{q}_0^H \mathbf{R}_1 \mathbf{q}_0 &= N|\alpha_{00}|^2 \quad \text{and} \quad \mathbf{q}_0^H \mathbf{R}_2 \mathbf{q}_0 = N|\alpha_{01}|^2 \\ \mathbf{q}_1^H \mathbf{R}_1 \mathbf{q}_1 &= N|\alpha_{10}|^2 \quad \text{and} \quad \mathbf{q}_1^H \mathbf{R}_2 \mathbf{q}_1 = N|\alpha_{11}|^2\end{aligned}$$

and our maximization equation (3) becomes:

$$\max_{\|\mathbf{q}_0\|=1} \mathbf{q}_0^H \mathbf{R} \mathbf{q}_0 = \max_{\|\mathbf{q}_0\|=1} [\sigma_1^2 + N(\sigma_1^2 |\alpha_{00}|^2 + \sigma_2^2 |\alpha_{01}|^2)]$$

If $\sigma_1^2 > \sigma_2^2$ then $|\alpha_{00}| = 1$ and $|\alpha_{01}| = 0$ maximizes our expression, whereas if $\sigma_1^2 < \sigma_2^2$ then $|\alpha_{00}| = 0$ and $|\alpha_{01}| = 1$ is our solution. In the case when $\sigma_1^2 = \sigma_2^2$ then the expression becomes independent of α_{00} and α_{01} and any unit length vector in our 2-dimensional subspace will be an eigenvector. Similarly for (4).

P4.14. (i)

$$\begin{aligned}\mathbf{w}^H \mathbf{R} \mathbf{w} &= (\mathbf{w}_R^T - j\mathbf{w}_I^T)(\mathbf{R}_R + j\mathbf{R}_I)(\mathbf{w}_R + j\mathbf{w}_I) \\ &= \mathbf{w}_R^T \mathbf{R}_R \mathbf{w}_R + j\mathbf{w}_R^T \mathbf{R}_R \mathbf{w}_I + j\mathbf{w}_R^T \mathbf{R}_I \mathbf{w}_R - \mathbf{w}_R^T \mathbf{R}_I \mathbf{w}_I \\ &\quad - j\mathbf{w}_I^T \mathbf{R}_R \mathbf{w}_R + \mathbf{w}_I^T \mathbf{R}_R \mathbf{w}_I + \mathbf{w}_I^T \mathbf{R}_I \mathbf{w}_R + j\mathbf{w}_I^T \mathbf{R}_I \mathbf{w}_I\end{aligned}$$

using the hint that $\mathbf{v}^T \mathbf{R}_I \mathbf{v} = 0$ and noticing the 2nd and 5th terms are negative of each other gives

$$\begin{aligned}\mathbf{w}^H \mathbf{R} \mathbf{w} &= \mathbf{w}_R^T \mathbf{R}_R \mathbf{w}_R + \mathbf{w}_I^T \mathbf{R}_R \mathbf{w}_I + \mathbf{w}_I^T \mathbf{R}_I \mathbf{w}_R - \mathbf{w}_R^T \mathbf{R}_I \mathbf{w}_I \\ &= \begin{bmatrix} \mathbf{w}_R^T & \mathbf{w}_I^T \end{bmatrix} \begin{bmatrix} \mathbf{R}_R \mathbf{w}_R & -\mathbf{R}_I \mathbf{w}_I \\ \mathbf{R}_I \mathbf{w}_R & \mathbf{R}_R \mathbf{w}_I \end{bmatrix} \\ &= \begin{bmatrix} \mathbf{w}_R^T & \mathbf{w}_I^T \end{bmatrix} \begin{bmatrix} \mathbf{R}_R & -\mathbf{R}_I \\ \mathbf{R}_I & \mathbf{R}_R \end{bmatrix} \begin{bmatrix} \mathbf{w}_R \\ \mathbf{w}_I \end{bmatrix}\end{aligned}$$

(ii)

$$\mathbf{R} \mathbf{q}_i = (\mathbf{R}_R + j\mathbf{R}_I)(\mathbf{q}_{i,R} + j\mathbf{q}_{i,I}) = \lambda_i \mathbf{q}_i$$

$$\mathbf{R}_R \mathbf{q}_{i,R} + j\mathbf{R}_R \mathbf{q}_{i,I} + j\mathbf{R}_I \mathbf{q}_{i,R} - \mathbf{R}_I \mathbf{q}_{i,I} = \lambda_i (\mathbf{q}_{i,R} + j\mathbf{q}_{i,I})$$

Equating real and imaginary parts of both sides gives

$$\begin{aligned}\mathbf{R}_R \mathbf{q}_{i,R} - \mathbf{R}_I \mathbf{q}_{i,I} &= \lambda_i \mathbf{q}_{i,R} \\ \mathbf{R}_R \mathbf{q}_{i,I} + \mathbf{R}_I \mathbf{q}_{i,R} &= \lambda_i \mathbf{q}_{i,I}\end{aligned}$$

which is equivalent to

$$\begin{bmatrix} \mathbf{R}_R & -\mathbf{R}_I \\ \mathbf{R}_I & \mathbf{R}_R \end{bmatrix} \begin{bmatrix} \mathbf{q}_{i,R} \\ \mathbf{q}_{i,I} \end{bmatrix} = \lambda_i \begin{bmatrix} \mathbf{q}_{i,R} \\ \mathbf{q}_{i,I} \end{bmatrix}$$

Also,

$$\mathbf{R}(j\mathbf{q}_i) = \lambda_i(j\mathbf{q}_i)$$