

Structured Matrix Computations

- ① Basic Structures for One-Dimensional Problems
 - the role of boundary conditions
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 - periodic boundary conditions
- ③ Symmetric Toeplitz-plus-Hankel Matrices
 - reflexive boundary conditions
- ④ Kronecker Product Matrices
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- ⑤ Summary of Fast Algorithms
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The Linear Deblurring Model

$$\mathbf{b} = \mathbf{A} \mathbf{x} + \mathbf{e}$$

- Given:
a blurred and noisy image
 $\mathbf{b} = \text{vec}(\mathbf{B})$
and a BIG blurring matrix \mathbf{A} .
- Goal:
Compute an *approximation*
of the true image $\mathbf{x} = \text{vec}(\mathbf{X})$.



Useful Matrix Factorizations

Singular Value Decomposition (SVD)

$$\mathbf{A} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^T$$

where all matrices are *real*

- $\mathbf{\Sigma} = \text{diag}(\sigma_1, \sigma_2, \dots, \sigma_N)$, $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_N \geq 0$
- $\mathbf{U} = [\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_N]$, $\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_N]$
- $\mathbf{U}^T \mathbf{U} = \mathbf{I}$, $\mathbf{V}^T \mathbf{V} = \mathbf{I}$

Spectral Decomposition

$$\mathbf{A} = \tilde{\mathbf{U}} \mathbf{\Lambda} \tilde{\mathbf{U}}^*$$

where the matrices are usually *complex*

- $\mathbf{\Lambda} = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_N)$ – no ordering
- $\tilde{\mathbf{U}} = [\tilde{\mathbf{u}}_1, \tilde{\mathbf{u}}_2, \dots, \tilde{\mathbf{u}}_N]$
- $\tilde{\mathbf{U}}^* \tilde{\mathbf{U}} = \mathbf{I}$, where $\tilde{\mathbf{U}}^* =$ complex conjugate of $\tilde{\mathbf{U}}^T$

Chapter Goal

The SVD and Spectral Decomposition can be used to:

- Investigate sensitivity of image deblurring problem
→ Chapter 5.
- Construct image deblurring algorithms
→ Chapter 6.

To compute these decompositions efficiently for large matrices, we must *exploit structure* → this chapter.

Question: What is the matrix **A** and how do we get it?

Basic Structures: One-Dimensional Problems

Recall:

Each blurred pixel is a weighted sum of the corresponding pixel and its neighbors in the true image.

For example, if

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \quad \text{and} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix}$$

then

$$b_3 = \square x_1 + \square x_2 + \square x_3 + \square x_4 + \square x_5$$

The weights come from the PSF.

An example, \mathbf{p} = PSF array, $\mathbf{b} = \mathbf{A} \mathbf{x}$ = sum of weighted PSF's:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}, \quad \mathbf{p} = \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \\ p_5 \end{bmatrix} \quad \text{and} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix}$$

$$\mathbf{b} = \begin{bmatrix} p_3 \\ p_4 \\ p_5 \\ 0 \\ 0 \end{bmatrix} x_1 + \begin{bmatrix} p_2 \\ p_3 \\ p_4 \\ p_5 \\ 0 \end{bmatrix} x_2 + \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \\ p_5 \end{bmatrix} x_3 + \begin{bmatrix} 0 \\ p_1 \\ p_2 \\ p_3 \\ p_4 \end{bmatrix} x_4 + \begin{bmatrix} 0 \\ 0 \\ p_1 \\ p_2 \\ p_3 \end{bmatrix} x_5$$

1. "Rotate" the PSF \mathbf{p} 180 degrees about center:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}, \quad \begin{bmatrix} p_5 \\ p_4 \\ p_3 \\ p_2 \\ p_1 \end{bmatrix} \quad \text{and} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix}$$

2. Match coefficients of rotated PSF and \mathbf{x} :

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \quad \begin{bmatrix} p_5 \\ p_4 \\ p_3 \\ p_2 \\ p_1 \end{bmatrix} \quad \text{and} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix}$$

3. Multiply corresponding components and sum them:

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \begin{bmatrix} p_5 \\ p_4 \\ p_3 \\ p_2 \\ p_1 \end{bmatrix} \quad \text{and} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix}$$

to obtain

$$b_3 = p_5x_1 + p_4x_2 + p_3x_3 + p_2x_4 + p_1x_5$$

This is *one-dimensional convolution*.

Same idea when \mathbf{x} is longer than \mathbf{p} :

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \\ x_9 \end{bmatrix} \begin{bmatrix} p_5 \\ p_4 \\ p_3 \\ p_2 \\ p_1 \end{bmatrix} \quad \text{and} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \\ b_6 \\ b_7 \\ b_8 \\ b_9 \end{bmatrix}$$

where we obtain from the convolution

$$b_5 = p_5x_3 + p_4x_4 + p_3x_5 + p_2x_6 + p_1x_7$$

If the weights fall outside the true image scene:

$$\begin{bmatrix} ? \\ x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \begin{bmatrix} p_5 \\ p_4 \\ p_3 \\ p_2 \\ p_1 \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix}$$

then

$$b_2 = p_5 \underline{?} + p_4 x_1 + p_3 x_2 + p_2 x_3 + p_1 x_4$$

Impose boundary conditions:

$$\begin{bmatrix} w \\ x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \begin{bmatrix} p_5 \\ p_4 \\ p_3 \\ p_2 \\ p_1 \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix}$$

then

$$b_2 = p_5 w + p_4 x_1 + p_3 x_2 + p_2 x_3 + p_1 x_4$$

Impose boundary conditions, such as **zero**

$$\begin{bmatrix} 0 \\ x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \begin{bmatrix} p_5 \\ p_4 \\ p_3 \\ p_2 \\ p_1 \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix}$$

then

$$b_2 = p_4 x_1 + p_3 x_2 + p_2 x_3 + p_1 x_4$$

Impose boundary conditions, such as **periodic**

$$\begin{bmatrix} x_5 \\ x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \begin{bmatrix} p_5 \\ p_4 \\ p_3 \\ p_2 \\ p_1 \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix}$$

then

$$b_2 = p_5 x_5 + p_4 x_1 + p_3 x_2 + p_2 x_3 + p_1 x_4$$

Impose boundary conditions, such as **reflexive**

$$\begin{bmatrix} x_1 \\ x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \begin{bmatrix} p_5 \\ p_4 \\ p_3 \\ p_2 \\ p_1 \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix}$$

then

$$b_2 = p_5x_1 + p_4x_1 + p_3x_2 + p_2x_3 + p_1x_4$$

In General, We Can Write

$$\begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix} = \begin{bmatrix} p_5 & p_4 & p_3 & p_2 & p_1 & & & & & & \\ & p_5 & p_4 & p_3 & p_2 & p_1 & & & & & \\ & & p_5 & p_4 & p_3 & p_2 & p_1 & & & & \\ & & & p_5 & p_4 & p_3 & p_2 & p_1 & & & \\ & & & & p_5 & p_4 & p_3 & p_2 & p_1 & & \\ & & & & & p_5 & p_4 & p_3 & p_2 & p_1 & \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \hline x_1 \\ x_2 \\ x_3 \\ x_4 \\ \hline x_5 \\ y_1 \\ y_2 \end{bmatrix}$$

- “empty element” denotes 0
- zero BC $\Rightarrow w_i = y_i = 0$
- periodic BC $\Rightarrow w_1 = x_4, w_2 = x_5, y_1 = x_1, y_2 = x_2$
- reflexive BC $\Rightarrow w_1 = x_2, w_2 = x_1, y_1 = x_5, y_2 = x_4$

Therefore, for **zero** boundary conditions we get:

$$\begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix} = \begin{bmatrix} p_3 & p_2 & p_1 & & & \\ p_4 & p_3 & p_2 & p_1 & & \\ p_5 & p_4 & p_3 & p_2 & p_1 & \\ & p_5 & p_4 & p_3 & p_2 & \\ & & p_5 & p_4 & p_3 & \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}$$

Here **A** is a *Toeplitz matrix*.

Note that

- the middle column is identical to **p**, and
- the middle row $[p_5 \ p_4 \ p_3 \ p_2 \ p_1]$ consists of the elements of **p** in reverse order.

For **periodic** boundary conditions we get:

$$\begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix} = \begin{bmatrix} p_3 & p_2 & p_1 & p_5 & p_4 \\ p_4 & p_3 & p_2 & p_1 & p_5 \\ p_5 & p_4 & p_3 & p_2 & p_1 \\ p_1 & p_5 & p_4 & p_3 & p_2 \\ p_2 & p_1 & p_5 & p_4 & p_3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}$$

Here **A** is a *circulant matrix*.

For **reflexive** boundary conditions we get:

$$\begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \\ b_5 \end{bmatrix} = \left(\begin{bmatrix} p_3 & p_2 & p_1 & & \\ p_4 & p_3 & p_2 & p_1 & \\ p_5 & p_4 & p_3 & p_2 & p_1 \\ & p_5 & p_4 & p_3 & p_2 \\ & & p_5 & p_4 & p_3 \end{bmatrix} + \begin{bmatrix} p_4 & p_5 & & & \\ p_5 & & & & \\ & & & & \\ & & & p_1 & \\ p_1 & p_2 & & & \end{bmatrix} \right) \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}$$

Here **A** is a *Toeplitz-plus-Hankel matrix*.

Two-Dimensional Problems

As with one-dimensional problems, to compute pixel b_{ij} :

- 1 Rotate the PSF \mathbf{P} by 180 degrees.
- 2 Locate it at the desired position.
- 3 Match coefficients of rotated PSF and \mathbf{X} .
- 4 Multiply corresponding components and sum them.

For example, to compute b_{22}

$$\begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{bmatrix} \quad \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \quad \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

X **P** **B**

Rotate, multiply, and sum:

$$\begin{bmatrix} x_{11} & x_{12} & x_{13} \\ p_{33} & p_{32} & p_{31} \\ x_{21} & x_{22} & x_{23} \\ p_{23} & p_{22} & p_{21} \\ x_{31} & x_{32} & x_{33} \\ p_{13} & p_{12} & p_{11} \end{bmatrix} \quad \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

$$\begin{aligned} b_{22} = & p_{33}x_{11} + p_{32}x_{12} + p_{31}x_{13} + \\ & p_{23}x_{21} + p_{22}x_{22} + p_{21}x_{23} + \\ & p_{13}x_{31} + p_{12}x_{32} + p_{11}x_{33} \end{aligned}$$

Consider what happens at the edges:

$$\begin{array}{ccc} p_{33} & p_{32} & p_{31} \\ p_{23} & \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ p_{22} & p_{21} \end{bmatrix} \\ p_{13} & \begin{bmatrix} x_{21} & x_{22} & x_{23} \\ p_{12} & p_{11} \end{bmatrix} \\ & \begin{bmatrix} x_{31} & x_{32} & x_{33} \end{bmatrix} \end{array} \quad \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

$$\begin{aligned} b_{11} = & p_{33} \underline{\quad} + p_{32} \underline{\quad} + p_{31} \underline{\quad} + \\ & p_{23} \underline{\quad} + p_{22} x_{11} + p_{21} x_{12} + \\ & p_{13} \underline{\quad} + p_{12} x_{21} + p_{11} x_{22} \end{aligned}$$

Again, we need to impose boundary conditions:

$$\begin{array}{ccc} p_{33} & p_{32} & p_{31} \\ p_{23} & \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ p_{22} & p_{21} \end{bmatrix} \\ p_{13} & \begin{bmatrix} x_{21} & x_{22} & x_{23} \\ p_{12} & p_{11} \end{bmatrix} \\ & \begin{bmatrix} x_{31} & x_{32} & x_{33} \end{bmatrix} \end{array} \quad \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

Zero:

$$\begin{aligned} b_{11} = & p_{33} \underline{0} + p_{32} \underline{0} + p_{31} \underline{0} + \\ & p_{23} \underline{0} + p_{22} x_{11} + p_{21} x_{12} + \\ & p_{13} \underline{0} + p_{12} x_{21} + p_{11} x_{22} \end{aligned}$$

Again, we need to impose boundary conditions:

$$\begin{array}{ccc} p_{33} & p_{32} & p_{31} \\ p_{23} & \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ p_{22} & p_{21} \end{bmatrix} \\ p_{13} & \begin{bmatrix} x_{21} & x_{22} & x_{23} \\ p_{12} & p_{11} \end{bmatrix} \\ & \begin{bmatrix} x_{31} & x_{32} & x_{33} \end{bmatrix} \end{array} \quad \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

Periodic:

$$\begin{aligned} b_{11} = & p_{33} \underline{x_{33}} + p_{32} \underline{x_{31}} + p_{31} \underline{x_{32}} + \\ & p_{23} \underline{x_{13}} + p_{22} x_{11} + p_{21} x_{12} + \\ & p_{13} \underline{x_{23}} + p_{12} x_{21} + p_{11} x_{22} \end{aligned}$$

Again, we need to impose boundary conditions:

$$\begin{array}{ccc} p_{33} & p_{32} & p_{31} \\ p_{23} & \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ p_{22} & p_{21} \end{bmatrix} \\ p_{13} & \begin{bmatrix} x_{21} & x_{22} & x_{23} \\ p_{12} & p_{11} \end{bmatrix} \\ & \begin{bmatrix} x_{31} & x_{32} & x_{33} \end{bmatrix} \end{array} \quad \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

Reflexive:

$$\begin{aligned} b_{11} = & p_{33} \underline{x_{11}} + p_{32} \underline{x_{11}} + p_{31} \underline{x_{12}} + \\ & p_{23} \underline{x_{11}} + p_{22} x_{11} + p_{21} x_{12} + \\ & p_{13} \underline{x_{21}} + p_{12} x_{21} + p_{11} x_{22} \end{aligned}$$

Matrix Structures

- Zero boundary conditions $\Rightarrow A$ is BTTB
- Periodic boundary conditions $\Rightarrow A$ is BCCB
- Reflexive boundary conditions $\Rightarrow A$ is sum of BTTB, BTHB, BHTB, and BHBB (notation: $B_{HT}^{TT} + B_{HH}^{TH}$?)

Legend:

BTTB: Block Toeplitz with Toeplitz blocks

BCCB: Block circulant with circulant blocks

BTHB: Block Toeplitz with Hankel blocks

BHTB: Block Hankel with Toeplitz blocks

BHBB: Block Hankel with Hankel blocks

Zero Boundary Conditions \Rightarrow BTTB matrix

$$\begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \\ \hline b_{12} \\ b_{22} \\ b_{32} \\ \hline b_{13} \\ b_{23} \\ b_{33} \end{bmatrix} = \begin{bmatrix} \begin{array}{cc|cc} p_{22} & p_{12} & p_{21} & p_{11} \\ p_{32} & p_{22} & p_{12} & p_{31} & p_{21} & p_{11} \\ & p_{32} & p_{22} & & p_{31} & p_{21} \end{array} \\ \hline \begin{array}{cc|cc} p_{23} & p_{13} & p_{22} & p_{12} \\ p_{33} & p_{23} & p_{32} & p_{22} & p_{12} & p_{11} \\ & p_{33} & p_{23} & & p_{31} & p_{21} \end{array} \\ \hline \begin{array}{cc|cc} & & p_{23} & p_{13} \\ & & p_{33} & p_{23} & p_{13} & p_{12} \\ & & & p_{33} & p_{23} & p_{22} \end{array} \end{array} \begin{bmatrix} x_{11} \\ x_{21} \\ x_{31} \\ \hline x_{12} \\ x_{22} \\ x_{32} \\ \hline x_{13} \\ x_{23} \\ x_{33} \end{bmatrix}$$

$$\mathbf{b} = \text{vec}(\mathbf{B}),$$

$$\mathbf{p} = \text{vec}(\mathbf{P}),$$

$$\mathbf{x} = \text{vec}(\mathbf{X})$$

Periodic Boundary Conditions \Rightarrow BCCB matrix

$$\begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \\ \hline b_{12} \\ b_{22} \\ b_{32} \\ \hline b_{13} \\ b_{23} \\ b_{33} \end{bmatrix} = \begin{bmatrix} p_{22} & p_{12} & p_{32} & p_{21} & p_{11} & p_{31} & p_{23} & p_{13} & p_{33} \\ p_{32} & p_{22} & p_{12} & p_{31} & p_{21} & p_{11} & p_{33} & p_{23} & p_{13} \\ p_{12} & p_{32} & p_{22} & p_{11} & p_{31} & p_{21} & p_{13} & p_{33} & p_{23} \\ \hline p_{23} & p_{13} & p_{33} & p_{22} & p_{12} & p_{32} & p_{21} & p_{11} & p_{31} \\ p_{33} & p_{23} & p_{13} & p_{32} & p_{22} & p_{12} & p_{31} & p_{21} & p_{11} \\ p_{13} & p_{33} & p_{23} & p_{12} & p_{32} & p_{22} & p_{11} & p_{31} & p_{21} \\ \hline p_{21} & p_{11} & p_{31} & p_{23} & p_{13} & p_{33} & p_{22} & p_{12} & p_{32} \\ p_{31} & p_{21} & p_{11} & p_{33} & p_{23} & p_{13} & p_{32} & p_{22} & p_{12} \\ p_{11} & p_{31} & p_{21} & p_{13} & p_{33} & p_{23} & p_{12} & p_{32} & p_{22} \end{bmatrix} \begin{bmatrix} x_{11} \\ x_{21} \\ x_{31} \\ \hline x_{12} \\ x_{22} \\ x_{32} \\ \hline x_{13} \\ x_{23} \\ x_{33} \end{bmatrix}$$

$$\mathbf{b} = \text{vec}(\mathbf{B}),$$

$$\mathbf{p} = \text{vec}(\mathbf{P}),$$

$$\mathbf{x} = \text{vec}(\mathbf{X})$$

Reflexive Boundary Conditions $\Rightarrow \dots$

With **reflexive** boundary conditions \mathbf{A} is much more complicated.
For example, the first row of \mathbf{A} is:

$$[p_{22} + p_{23} + p_{32} + p_{33}, p_{12} + p_{13}, 0, p_{21} + p_{31}, p_{11}, 0, 0, 0, 0]$$

It can be shown that \mathbf{A} is a sum of four structured matrices, with BTTB, BTHB, BHTB, and BHHB structure, respectively.

Separable Blur

Horizontal and vertical components separate.

In this case, the PSF array has rank = 1:

$$\begin{aligned}\mathbf{P} = \mathbf{c}\mathbf{r}^T &= \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} \begin{bmatrix} r_1 & r_2 & r_3 \end{bmatrix} \\ &= \begin{bmatrix} c_1 r_1 & c_1 r_2 & c_1 r_3 \\ c_2 r_1 & c_2 r_2 & c_2 r_3 \\ c_3 r_1 & c_3 r_2 & c_3 r_3 \end{bmatrix}\end{aligned}$$

Separable Blur

Forming the matrix with this special PSF we obtain (zero BC):

$$\mathbf{A} = \left[\begin{array}{cc|cc} c_2 r_2 & c_1 r_2 & c_2 r_1 & c_1 r_1 \\ c_3 r_2 & c_2 r_2 & c_1 r_2 & c_3 r_1 & c_2 r_1 & c_1 r_1 \\ & c_3 r_2 & c_2 r_2 & & c_3 r_1 & c_2 r_1 \\ \hline c_2 r_3 & c_1 r_3 & & c_2 r_2 & c_1 r_2 & & c_2 r_1 & c_1 r_1 \\ c_3 r_3 & c_2 r_3 & c_1 r_3 & c_3 r_2 & c_2 r_2 & c_1 r_2 & c_3 r_1 & c_2 r_1 & c_1 r_1 \\ & c_3 r_3 & c_2 r_3 & & c_3 r_2 & c_2 r_2 & & c_3 r_1 & c_2 r_1 \\ \hline & & & c_2 r_3 & c_1 r_3 & & c_2 r_2 & c_1 r_2 & \\ & & & c_3 r_3 & c_2 r_3 & c_1 r_3 & c_3 r_2 & c_2 r_2 & c_1 r_2 \\ & & & & c_3 r_3 & c_2 r_3 & & c_3 r_2 & c_2 r_2 \end{array} \right]$$

Separable Blur

$$\mathbf{A} = \left[\begin{array}{c|c|c} r_2 \begin{bmatrix} c_2 & c_1 \\ c_3 & c_2 & c_1 \\ & c_3 & c_2 \end{bmatrix} & r_1 \begin{bmatrix} c_2 & c_1 \\ c_3 & c_2 & c_1 \\ & c_3 & c_2 \end{bmatrix} & 0 \\ \hline r_3 \begin{bmatrix} c_2 & c_1 \\ c_3 & c_2 & c_1 \\ & c_3 & c_2 \end{bmatrix} & r_2 \begin{bmatrix} c_2 & c_1 \\ c_3 & c_2 & c_1 \\ & c_3 & c_2 \end{bmatrix} & r_1 \begin{bmatrix} c_2 & c_1 \\ c_3 & c_2 & c_1 \\ & c_3 & c_2 \end{bmatrix} \\ \hline 0 & r_3 \begin{bmatrix} c_2 & c_1 \\ c_3 & c_2 & c_1 \\ & c_3 & c_2 \end{bmatrix} & r_2 \begin{bmatrix} c_2 & c_1 \\ c_3 & c_2 & c_1 \\ & c_3 & c_2 \end{bmatrix} \end{array} \right]$$

Separable Blur

We see that for this special PSF we obtain (with zero BC):

$$\mathbf{A} = \mathbf{A}_r \otimes \mathbf{A}_c = \begin{bmatrix} r_2 & r_1 & & \\ r_3 & r_2 & r_1 & \\ & r_3 & r_2 & \end{bmatrix} \otimes \begin{bmatrix} c_2 & c_1 & & \\ c_3 & c_2 & c_1 & \\ & c_3 & c_2 & \end{bmatrix}$$

Here \otimes denotes the *Kronecker product*.

The Wonderful World of Kronecker Products

Definition:

$$\mathbf{A}_r = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \Rightarrow \mathbf{A}_r \otimes \mathbf{A}_c = \begin{bmatrix} a_{11}\mathbf{A}_c & a_{12}\mathbf{A}_c \\ a_{21}\mathbf{A}_c & a_{22}\mathbf{A}_c \end{bmatrix}$$

Transposition and inversion:

$$\begin{aligned} (\mathbf{A}_r \otimes \mathbf{A}_c)^T &= \mathbf{A}_r^T \otimes \mathbf{A}_c^T \\ (\mathbf{A}_r \otimes \mathbf{A}_c)^{-1} &= \mathbf{A}_r^{-1} \otimes \mathbf{A}_c^{-1} \end{aligned}$$

SVD:

$$(\mathbf{U}_r \Sigma_r \mathbf{V}_r^T) \otimes (\mathbf{U}_c \Sigma_c \mathbf{V}_c^T) = (\mathbf{U}_r \otimes \mathbf{U}_c) (\Sigma_r \otimes \Sigma_c) (\mathbf{V}_r \otimes \mathbf{V}_c)^T$$

Matrix-vector product:

$$(\mathbf{A}_r \otimes \mathbf{A}_c) \text{vec}(\mathbf{X}) = \text{vec}(\mathbf{A}_c \mathbf{X} \mathbf{A}_r^T)$$

Separable Blur with Boundary Conditions

Similar structures occur for other boundary conditions:

$$\mathbf{A} = \mathbf{A}_r \otimes \mathbf{A}_c$$

- Zero boundary conditions:
 - \mathbf{A}_r is Toeplitz, defined by \mathbf{r}
 - \mathbf{A}_c is Toeplitz, defined by \mathbf{c}
- Periodic boundary conditions:
 - \mathbf{A}_r is circulant, defined by \mathbf{r}
 - \mathbf{A}_c is circulant, defined by \mathbf{c}
- Reflexive boundary conditions:
 - \mathbf{A}_r is Toeplitz-plus-Hankel, defined by \mathbf{r}
 - \mathbf{A}_c is Toeplitz-plus-Hankel, defined by \mathbf{c}

Summary of Matrix Structures

BC	Non-separable PSF	Separable PSF
zero	BTTB	Kronecker product of Toeplitz matrices
periodic	BCCB	Kronecker product of circulant matrices
reflexive	BTTB+BTHB +BHTB+BHHB	Kronecker product of Toeplitz-plus-Hankel matrices

Computations with BCCB Matrices

Recall that with periodic boundary conditions \mathbf{A} is a BCCB matrix:

$$\begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \\ \hline b_{12} \\ b_{22} \\ b_{32} \\ \hline b_{13} \\ b_{23} \\ b_{33} \end{bmatrix} = \begin{bmatrix} p_{22} & p_{12} & p_{32} & | & p_{21} & p_{11} & p_{31} & | & p_{23} & p_{13} & p_{33} \\ p_{32} & p_{22} & p_{12} & | & p_{31} & p_{21} & p_{11} & | & p_{33} & p_{23} & p_{13} \\ p_{12} & p_{32} & p_{22} & | & p_{11} & p_{31} & p_{21} & | & p_{13} & p_{33} & p_{23} \\ \hline p_{23} & p_{13} & p_{33} & | & p_{22} & p_{12} & p_{32} & | & p_{21} & p_{11} & p_{31} \\ p_{33} & p_{23} & p_{13} & | & p_{32} & p_{22} & p_{12} & | & p_{31} & p_{21} & p_{11} \\ p_{13} & p_{33} & p_{23} & | & p_{12} & p_{32} & p_{22} & | & p_{11} & p_{31} & p_{21} \\ \hline p_{21} & p_{11} & p_{31} & | & p_{23} & p_{13} & p_{33} & | & p_{22} & p_{12} & p_{32} \\ p_{31} & p_{21} & p_{11} & | & p_{33} & p_{23} & p_{13} & | & p_{32} & p_{22} & p_{12} \\ p_{11} & p_{31} & p_{21} & | & p_{13} & p_{33} & p_{23} & | & p_{12} & p_{32} & p_{22} \end{bmatrix} \begin{bmatrix} x_{11} \\ x_{21} \\ x_{31} \\ \hline x_{12} \\ x_{22} \\ x_{32} \\ \hline x_{13} \\ x_{23} \\ x_{33} \end{bmatrix}$$

$$\mathbf{b} = \text{vec}(\mathbf{B}),$$

$$\mathbf{p} = \text{vec}(\mathbf{P}),$$

$$\mathbf{x} = \text{vec}(\mathbf{X})$$

The One-Dimensional Discrete Fourier Transform

If $\mathbf{x} \in \mathbb{R}^n$ then $\hat{\mathbf{x}} = DFT(\mathbf{x}) \in \mathbb{C}^n$ is defined by

$$\hat{x}_k = \frac{1}{\sqrt{n}} \sum_{j=1}^n x_j \exp(-2\pi i(j-1)(k-1)/n), \quad i = \sqrt{-1}.$$

There exists a unitary matrix $\mathbf{F}_n \in \mathbb{C}^{n \times n}$ such that

$$\hat{\mathbf{x}} = \sqrt{n} \mathbf{F}_n \mathbf{x} \quad \Leftrightarrow \quad \mathbf{x} = \frac{1}{\sqrt{n}} \mathbf{F}_n^* \hat{\mathbf{x}}$$

in which $\mathbf{F}_n^* = \text{conj}(\mathbf{F}_n)^T$.

The Two-Dimensional DFT

If $\mathbf{X} \in \mathbb{C}^{m \times n}$ then the 2-D DFT is defined by

$$\hat{\mathbf{X}} = (\sqrt{m} \mathbf{F}_m) \mathbf{X} (\sqrt{n} \mathbf{F}_n)^* = \sqrt{N} \mathbf{F}_m \mathbf{X} \mathbf{F}_n^*$$

with $N = m n$ (1-D DFTs along the columns and rows of \mathbf{X}).

From the Kronecker product relations we get

$$\text{vec}(\hat{\mathbf{X}}) = \sqrt{N} (\text{conj}(\mathbf{F}_n) \otimes \mathbf{F}_m) \text{vec}(\mathbf{X}) = \sqrt{N} \mathbf{F} \text{vec}(\mathbf{X}) ,$$

where $\mathbf{F} = \text{conj}(\mathbf{F}_n) \otimes \mathbf{F}_m$.

Important BCCB Matrix Property

- Every BCCB matrix has the same set of eigenvectors:

$$\mathbf{A} = \mathbf{F}^* \mathbf{\Lambda} \mathbf{F} \quad \left(= \mathbf{F}^* \mathbf{\Lambda} (\mathbf{F}^*)^* \right)$$

where

- \mathbf{F} is the two-dimensional discrete Fourier transform matrix
 - \mathbf{F} is complex
 - \mathbf{F} is unitary: $\mathbf{F}^* \mathbf{F} = \mathbf{F} \mathbf{F}^* = \mathbf{I}$
 - \mathbf{F}^* is the matrix of eigenvectors of \mathbf{A}
 - $\mathbf{\Lambda}$ = diagonal complex matrix containing eigenvalues of \mathbf{A}
- Computations with \mathbf{F} can be done very efficiently:
 - \mathbf{F} times a vector requires $O(N \log N)$ flops using the 2-D Fast Fourier Transform (FFT) algorithm.

FFT Computations

In Matlab, if $\mathbf{A} = \mathbf{F}^* \mathbf{\Lambda} \mathbf{F}$ is $N \times N$, then:

- $\text{fft2} \leftrightarrow \sqrt{N} \mathbf{F}$ and $\text{ifft2} \leftrightarrow \frac{1}{\sqrt{N}} \mathbf{F}^*$
- Specifically, the following operations are equivalent:
 - $\sqrt{N} \mathbf{F} \mathbf{x} \leftrightarrow \text{fft2}(\mathbf{X})$
 - $\frac{1}{\sqrt{N}} \mathbf{F}^* \mathbf{x} \leftrightarrow \text{ifft2}(\mathbf{X})$

where $\mathbf{x} = \text{vec}(\mathbf{X})$, and \mathbf{X} is $m \times n$ with $N = mn$.

Eigenvalues of BCCB Matrix

$$\mathbf{A} = \mathbf{F}^* \mathbf{\Lambda} \mathbf{F} \Rightarrow \mathbf{F} \mathbf{A} = \mathbf{\Lambda} \mathbf{F} \Rightarrow \mathbf{F} \mathbf{a}_1 = \mathbf{\Lambda} \mathbf{f}_1$$

where

- \mathbf{a}_1 = first column of \mathbf{A}
- \mathbf{f}_1 = first column of \mathbf{F} :

$$\mathbf{f}_1 = \frac{1}{\sqrt{N}} \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$$

- Thus

$$\mathbf{F} \mathbf{a}_1 = \mathbf{\Lambda} \mathbf{f}_1 = \frac{1}{\sqrt{N}} \boldsymbol{\lambda}$$

where $\boldsymbol{\lambda}$ is a vector containing the eigenvalues of \mathbf{A} .

Computing the Eigenvalues of BCCB Matrix

Thus, to compute eigenvalues of \mathbf{A} , we need to:

- Multiply the matrix $\sqrt{N}\mathbf{F}$ by the first column of \mathbf{A} .
- Or, equivalently, apply `fft2` to a two-dimensional array containing the elements of the first column of \mathbf{A} .
- Can get this array from the PSF:

$$\left[\begin{array}{c|cc} p_{11} & p_{12} & p_{13} \\ \hline p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{array} \right] \longleftrightarrow \left[\begin{array}{cc|c} p_{22} & p_{23} & p_{21} \\ \hline p_{32} & p_{33} & p_{31} \\ p_{12} & p_{13} & p_{11} \end{array} \right]$$

\mathbf{P}

first column of \mathbf{A}
`circshift(P, 1-[2,2])`

Efficient BCCB Computations

Thus, for zero boundary conditions, we have a BCCB matrix defined by:

- the PSF array **P**
- the center of PSF = [row, col]

To compute eigenvalues (spectral values) in this case:

```
S = fft2( circshift(P, 1-center) );
```

Note that **S** is an array, not a vector, and eigenvalues are not sorted.

Additional BCCB Computations

If \mathbf{A} is the BCCB matrix defined by the PSF array \mathbf{P} , and

$$\mathbf{b} = \mathbf{A} \mathbf{x} = \mathbf{F}^* \Lambda \mathbf{F} \mathbf{x}$$

then to compute \mathbf{b} use

```
S = fft2( circshift(P, 1 - center) );  
B = ifft2(S .* fft2(X));  
B = real(B);
```

where

$$\mathbf{b} = \text{vec}(\mathbf{B}) \quad \text{and} \quad \mathbf{x} = \text{vec}(\mathbf{X}) .$$

Small PSF Arrays. If the PSF array \mathbf{P} is *smaller* than the \mathbf{B} and \mathbf{X} images, then use our Matlab function `padPSF` to embed the $p \times q$ array \mathbf{P} in a larger array of size $m \times n$.

Additional BCCB Computations

If \mathbf{A} is the BCCB matrix defined by the PSF array \mathbf{P} , and

$$\mathbf{x}_{\text{naive}} = \mathbf{A}^{-1}\mathbf{b} = \mathbf{F}^* \mathbf{\Lambda}^{-1} \mathbf{F} \mathbf{b}$$

then to compute \mathbf{x} use

```
S = fft2( circshift(P, 1 - center) );  
X = ifft2(fft2(B) ./ S);  
X = real(X);
```

where

$$\mathbf{b} = \text{vec}(\mathbf{B}) \quad \text{and} \quad \mathbf{x} = \text{vec}(\mathbf{X}) .$$

BTTB+BTHB+BHTB+BHHB Matrices

With reflexive boundary conditions \mathbf{A} is a

$$\mathbf{BTTB} + \mathbf{BTHB} + \mathbf{BHTB} + \mathbf{BHHB}$$

matrix defined by the PSF.

Double symmetry condition: if

$$\mathbf{P} = \begin{bmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{P}} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}$$

where

- $\tilde{\mathbf{P}}$ is $(2k - 1) \times (2k - 1)$ with center located at (k, k)
- $\tilde{\mathbf{P}} = \text{fliplr}(\tilde{\mathbf{P}}) = \text{flipud}(\tilde{\mathbf{P}})$

BTTB+BTHB+BHTB+BHHB Matrix Properties

If the PSF satisfies the double symmetry condition, then:

- \mathbf{A} is symmetric
- \mathbf{A} is block symmetric
- Each block in \mathbf{A} is symmetric
- \mathbf{A} has the spectral decomposition

$$\mathbf{A} = \mathbf{C}^T \mathbf{\Lambda} \mathbf{C}$$

where \mathbf{C} is the two-dimensional discrete cosine transform (DCT) matrix.

- \mathbf{C} is real, and \mathbf{C}^T contains the eigenvectors.
- As with FFTs, computations with \mathbf{C} cost $O(N \log N)$ flops.

DCT Computations

With Matlab's the image processing toolbox, if $\mathbf{A} = \mathbf{C}^T \mathbf{\Lambda} \mathbf{C}$ is $N \times N$, then:

- $\text{dct2} \leftrightarrow \mathbf{C}$ and $\text{idct2} \leftrightarrow \mathbf{C}^T$
- Specifically, the following operations are equivalent:
 - $\mathbf{C} \mathbf{x} \leftrightarrow \text{dct2}(\mathbf{X})$
 - $\mathbf{C}^T \mathbf{x} \leftrightarrow \text{idct2}(\mathbf{X})$

where $\mathbf{x} = \text{vec}(\mathbf{X})$, and \mathbf{X} is $m \times n$ with $N = mn$.

Without the image processing toolbox, use our codes:

- $\text{dct2} \rightarrow \text{dcts2}$ and $\text{idct2} \rightarrow \text{idcts2}$.

DCT Relations and Eigenvalues

$$\mathbf{A} = \mathbf{C}^T \mathbf{\Lambda} \mathbf{C} \Rightarrow \mathbf{C} \mathbf{A} = \mathbf{\Lambda} \mathbf{C} \Rightarrow \mathbf{C} \mathbf{a}_1 = \mathbf{\Lambda} \mathbf{c}_1$$

where

- \mathbf{a}_1 = first column of \mathbf{A}
- \mathbf{c}_1 = first column of \mathbf{C} ,
- Thus, the eigenvalues of \mathbf{C} are given by

$$\mathbf{C} \mathbf{a}_1 = \mathbf{\Lambda} \mathbf{c}_1 \Rightarrow \lambda_i = \frac{[\mathbf{C} \mathbf{a}_1]_i}{[\mathbf{c}_1]_i}$$

More DCT Relations

Thus, to compute eigenvalues of \mathbf{A} , we need to:

- Multiply the matrix \mathbf{C} to the first column of \mathbf{A} .
- Or, equivalently, apply `dct2` to a two-dimensional array containing the elements of the first column of \mathbf{A} .
- Can get this array by adding four shifted PSFs, which we have implemented as:

```
dctshift(P, center)
```

- We also need the first column of \mathbf{C} , i.e., $\mathbf{c}_1 = \mathbf{C} \mathbf{e}_1$.
- Note that $\mathbf{e}_1 = \text{vec}(\mathbf{e}_1)$ with

```
e1 = zeros(m,n); e1(1,1) = 1;
```
- Thus we get the desired column via `dct2(e1)`.

Efficient Computations with DCT

Thus, for reflexive boundary conditions, with

- doubly symmetric PSF \mathbf{P}
- center of PSF = [row, col]

To compute eigenvalues (spectral values) in this case:

```
e1 = zeros(size(P)); e1(1,1) = 1;  
S = dct2( dctshift(P, center) ) ./ dct2(e1);
```

Additional DCT Computations

If \mathbf{A} is defined by a doubly symmetric PSF with reflexive boundary conditions, and

$$\mathbf{b} = \mathbf{A}\mathbf{x} = \mathbf{C}^T \mathbf{\Lambda} \mathbf{C}\mathbf{x}$$

then to compute \mathbf{b} use

```
e1 = zeros(size(P)); e1(1,1) = 1;  
S = dct2( dctshift(P, center) ) ./ dct2(e1);  
B = idct2(S .* dct2(X));
```

where

$$\mathbf{b} = \text{vec}(\mathbf{B}) \quad \text{and} \quad \mathbf{x} = \text{vec}(\mathbf{X})$$

Additional DCT Computations

If \mathbf{A} is defined by a doubly symmetric PSF with reflexive boundary conditions, and

$$\mathbf{x}_{\text{naive}} = \mathbf{A}^{-1}\mathbf{b} = \mathbf{C}^T \mathbf{\Lambda}^{-1} \mathbf{C} \mathbf{b}$$

then to compute \mathbf{x} use

```
e1 = zeros(size(P)); e1(1,1) = 1;  
S = dct2( dctshift(P, center) ) ./ dct2(e1);  
X = idct2(dct2(B) ./ S);
```

where

$$\mathbf{b} = \text{vec}(\mathbf{B}) \quad \text{and} \quad \mathbf{x} = \text{vec}(\mathbf{X})$$

Separable PSFs and Kronecker Products

Recall: If the PSF has rank = 1,

$$\mathbf{P} = \mathbf{c}\mathbf{r}^T = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_m \end{bmatrix} \begin{bmatrix} r_1 & r_2 & \cdots & r_n \end{bmatrix}$$

then the blurring matrix has the form

$$\mathbf{A} = \mathbf{A}_r \otimes \mathbf{A}_c$$

where \mathbf{A}_r is defined by \mathbf{r} and \mathbf{A}_c is defined by \mathbf{c} .

Assume for now \mathbf{A}_r and \mathbf{A}_c are known.

Exploiting Kronecker Product Properties

Using the property:

$$\mathbf{b} = (\mathbf{A}_r \otimes \mathbf{A}_c) \mathbf{x} \quad \Leftrightarrow \quad \mathbf{B} = \mathbf{A}_c \mathbf{X} \mathbf{A}_r^T$$

in Matlab we can compute

$$\mathbf{B} = \mathbf{A}_c * \mathbf{X} * \mathbf{A}_r';$$

Using the property:

$$\mathbf{b} = (\mathbf{A}_r \otimes \mathbf{A}_c) \mathbf{x} \quad \Leftrightarrow \quad \mathbf{B} = \mathbf{A}_c \mathbf{X} \mathbf{A}_r^T$$

and if \mathbf{A}_r and \mathbf{A}_c are nonsingular,

$$(\mathbf{A}_r \otimes \mathbf{A}_c)^{-1} = \mathbf{A}_r^{-1} \otimes \mathbf{A}_c^{-1}$$

we obtain

$$\mathbf{X} = \mathbf{A}_c^{-1} \mathbf{B} \mathbf{A}_r^{-T}$$

In Matlab we can compute

$$\mathbf{X} = \mathbf{A}_c \setminus \mathbf{B} / \mathbf{A}_r';$$

We can compute SVD of small matrices:

$$\mathbf{A}_r = \mathbf{U}_r \Sigma_r \mathbf{V}_r^T \quad \text{and} \quad \mathbf{A}_c = \mathbf{U}_c \Sigma_c \mathbf{V}_c^T$$

Then

$$\begin{aligned} \mathbf{A} &= \mathbf{A}_r \otimes \mathbf{A}_c \\ &= (\mathbf{U}_r \Sigma_r \mathbf{V}_r^T) \otimes (\mathbf{U}_c \Sigma_c \mathbf{V}_c^T) \\ &= (\mathbf{U}_r \otimes \mathbf{U}_c) (\Sigma_r \otimes \Sigma_c) (\mathbf{V}_r \otimes \mathbf{V}_c)^T \\ &= \text{SVD of big matrix } \mathbf{A} \end{aligned}$$

Note: Do not need to explicitly form the big matrices

$$\mathbf{U}_r \otimes \mathbf{U}_c, \quad \Sigma_r \otimes \Sigma_c, \quad \mathbf{V}_r \otimes \mathbf{V}_c$$

To compute inverse solution from SVD of small matrices:

$$\mathbf{x}_{\text{naive}} = \mathbf{A}^{-1}\mathbf{b} = \mathbf{V}\Sigma^{-1}\mathbf{U}^T\mathbf{b}$$

is equivalent to

$$\mathbf{X}_{\text{naive}} = \mathbf{A}_c^{-1}\mathbf{B}\mathbf{A}_r^{-T} = \mathbf{V}_c\Sigma_c^{-1}\mathbf{U}_c^T\mathbf{B}\mathbf{U}_r\Sigma_r^{-1}\mathbf{V}_r^T$$

A Matlab implementation could be:

```
[Ur, Sr, Vr] = svd(Ar);
```

```
[Uc, Sc, Vc] = svd(Ac);
```

```
S = diag(Sc) * diag(Sr)';
```

```
X = Vc * ( (Uc' * B * Ur) ./ S ) * Vr';
```

Getting \mathbf{A}_r and \mathbf{A}_c from the PSF Array

To construct \mathbf{A}_r and \mathbf{A}_c we must find \mathbf{r} and \mathbf{c} such that

$$\mathbf{P} = \mathbf{c}\mathbf{r}^T$$

- Compute the SVD: $\mathbf{P} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T = \sum_i \mathbf{u}_i \sigma_i \mathbf{v}_i^T$
- If \mathbf{P} has rank = 1, then $\sigma_2 = \sigma_3 = \dots = 0$, and

$$\mathbf{c} = \sqrt{\sigma_1} \mathbf{u}_1 \quad \mathbf{r} = \sqrt{\sigma_1} \mathbf{v}_1$$

- If \mathbf{P} has rank $\neq 1$, then

$$\mathbf{c} = \sqrt{\sigma_1} \mathbf{u}_1 \quad \mathbf{r} = \sqrt{\sigma_1} \mathbf{v}_1$$

give the approximations

$$\mathbf{P} \approx \mathbf{c}\mathbf{r}^T \quad \text{and} \quad \mathbf{A} \approx \mathbf{A}_r \otimes \mathbf{A}_c$$

Some Comments to the Matlab Code

- The singular vectors \mathbf{r} and \mathbf{c} can be computed using the `svd` or `svds` functions.
- Since we need at most two singular values, `svds` is convenient:

```
[U, S, V] = svds(P, 2);
```

If \mathbf{P} is $m \times n$ then \mathbf{U} is $m \times 2$, \mathbf{V} is $n \times 2$ and \mathbf{S} is 2×2 .

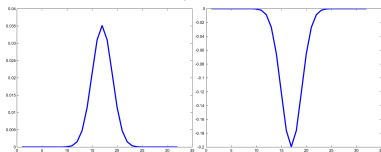
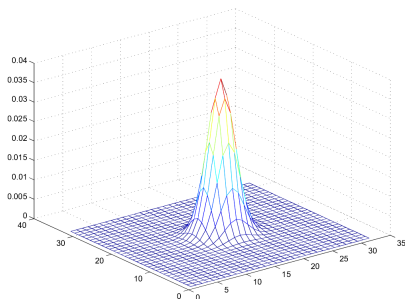
- Check to see if \mathbf{P} is separable. For example, if

```
S(2,2)/S(1,1) > small_tol
```

then \mathbf{P} is not separable.

A Matlab Example

- `P = psfGauss(32);`
- `mesh(P)`
- `plot(P(:,16])`
- `[U, S, V] = svds(P,2);`
- `c = sqrt(S(1,1))*U(:,1);`
- `r = sqrt(S(1,1))*V(:,1);`
- `mesh(c*r')`
- `plot(c)`



Check sign of singular vectors and change if necessary.

Construct \mathbf{A}_r and \mathbf{A}_c

Given \mathbf{r} and \mathbf{c} :

- zero BC: build Toeplitz \mathbf{A}_r , \mathbf{A}_c
- periodic BC: build circulant \mathbf{A}_r , \mathbf{A}_c
- reflexive BC: build Toeplitz-plus-Hankel \mathbf{A}_r , \mathbf{A}_c

Construct \mathbf{A}_r and \mathbf{A}_c for Zero BC in Matlab

Matlab function to build Toeplitz \mathbf{A}_r , \mathbf{A}_c , given

- middle column defining entries of matrix: $c = \mathbf{r}$ or \mathbf{c}
- loc. of center (diagonal) entry: $k = \text{center}(1)$ or $\text{center}(2)$

```
function T = buildToep(c, k)
    n = length(c);
    col = zeros(n,1); row = col;
    col(1:n-k+1) = c(k:n);
    row(1:k) = c(k:-1:1);
    T = toeplitz(col, row);
end
```

Then, given $P = \mathbf{c}*\mathbf{r}'$ and center of P,

```
Ac = buildToep(c, center(1));
Ar = buildToep(r, center(2));
```

Construct \mathbf{A}_r and \mathbf{A}_c for Periodic BC

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix}, \quad \text{center} = [2, 3]$$

Then, with periodic BC

$$\mathbf{A} = \mathbf{A}_r \otimes \mathbf{A}_c = \begin{bmatrix} r_3 & r_2 & r_1 & r_4 \\ r_4 & r_3 & r_2 & r_1 \\ r_1 & r_4 & r_3 & r_2 \\ r_2 & r_1 & r_4 & r_3 \end{bmatrix} \otimes \begin{bmatrix} c_2 & c_1 & c_3 \\ c_3 & c_2 & c_1 \\ c_1 & c_3 & c_2 \end{bmatrix}$$

If $k = 3 = \text{center}(2)$, then $\mathbf{A}_r = \text{toeplitz}(\text{col}, \text{row})$, where

$$\begin{aligned} \text{col} &= [r_k \quad r_{k+1} \quad \cdots \quad r_n \quad r_1 \quad \cdots \quad r_{k-1}] \\ \text{row} &= [r_k \quad r_{k-1} \quad \cdots \quad r_1 \quad r_n \quad \cdots \quad r_{k+1}] \end{aligned}$$

If $k = 2 = \text{center}(1)$, then $\mathbf{A}_c = \text{toeplitz}(\text{col}, \text{row})$, where

$$\begin{aligned} \text{col} &= [c_k \quad c_{k+1} \quad \cdots \quad c_n \quad c_1 \quad \cdots \quad c_{k-1}] \\ \text{row} &= [c_k \quad c_{k-1} \quad \cdots \quad c_1 \quad c_n \quad \cdots \quad c_{k+1}] \end{aligned}$$

$$\mathbf{A}_r = \begin{bmatrix} r_3 & r_2 & r_1 & r_4 \\ r_4 & r_3 & r_2 & r_1 \\ r_1 & r_4 & r_3 & r_2 \\ r_2 & r_1 & r_4 & r_3 \end{bmatrix} \quad \mathbf{A}_c = \begin{bmatrix} c_2 & c_1 & c_3 \\ c_3 & c_2 & c_1 \\ c_1 & c_3 & c_2 \end{bmatrix}$$

Construct \mathbf{A}_r and \mathbf{A}_c for Periodic BC in Matlab

Matlab function to build circulant \mathbf{A}_r , \mathbf{A}_c , given

- middle column defining entries of matrix: $\mathbf{c} = \mathbf{r}$ or \mathbf{c}
- loc. of center (diagonal) entry: $\mathbf{k} = \text{center}(1)$ or $\text{center}(2)$

```
function T = buildCirc(c, k)
    n = length(c);
    col = [c(k:n); c(1:k-1)];
    row = [c(k:-1:1); c(n:-1:k+1)];
    T = toeplitz(col, row);
end
```

Then, given $\mathbf{P} = \mathbf{c} * \mathbf{r}'$ and center of \mathbf{P}

```
Ac = buildCirc(c, center(1));
Ar = buildCirc(r, center(2));
```

Construct \mathbf{A}_r and \mathbf{A}_c for Reflexive BC

In this case

$$\mathbf{A} = \mathbf{A}_r \otimes \mathbf{A}_c$$

where

- $\mathbf{A}_r = \text{Toeplitz} + \text{Hankel}$
- $\mathbf{A}_c = \text{Toeplitz} + \text{Hankel}$
- Use `buildToep` for Toeplitz parts.
- How to get Hankel parts?

Construct \mathbf{A}_r and \mathbf{A}_c for Reflexive BC in Matlab

Matlab function to build Hankel part for \mathbf{A}_r , \mathbf{A}_c , given

- middle column defining entries of matrix: $c = \mathbf{r}$ or \mathbf{c}
- loc. of center (diagonal) entry: $k = \text{center}(1)$ or $\text{center}(2)$

```
function T = buildHank(c, k)
    n = length(c);
    col = zeros(n,1); row = col;
    col(1:n-k) = c(k+1:n);
    row(n-k+2:n) = c(1:k-1);
    T = hankel(col, row);
end
```

Then, given $P = \mathbf{c}*\mathbf{r}'$ and center of P

```
Ac = buildToep(c, center(1)) + buildHank(c, center(1));
```

```
Ar = buildToep(r, center(2)) + buildHank(r, center(2));
```


Construct \mathbf{A}_r and \mathbf{A}_c for All Three BC

```
[U, S, V] = svds(P, 2);  
c = sqrt(S(1,1))*U(:,1);  
r = sqrt(S(1,1))*V(:,1);  
switch BC  
  case 'zero'  
    Ac = buildToep(c, center(1));  
    Ar = buildToep(r, center(2));  
  case 'reflexive'  
    Ac = buildToep(c, center(1)) + buildHank(c, center(1));  
    Ar = buildToep(r, center(2)) + buildHank(r, center(2));  
  case 'periodic'  
    Ac = buildCirc(c, center(1));  
    Ar = buildCirc(r, center(2));  
end
```

Summary of Fast Algorithms

For spatially invariant PSFs, we have the following fast algorithms.

PSF	Boundary condition	Matrix structure	Fast algorithm
Arbitrary	Periodic	BCCB	2-dim FFT
Doubly sym.	Reflexive	BTTB+BTHB +BHTB+BHHB	2-dim DCT
Separable	Arbitrary	Kronecker product	2 small SVDs

Creating Realistic Test Data

Issues that must be considered:

- Small PSF.
- Creating blurred image without imposing artificial boundary conditions.
- Additive noise.

PSF Sizes

- It is often the case that
`size(P) < size(B)` and `size(X)`
- In this case we should “pad” `P` with zeros to increase size.
- Since we do this a lot, it is useful to have a function:

```
function Ppad = padPSF(P, size)
    Ppad = zeros(size);
    Ppad(1:size(P,1), 1:size(P,2)) = P;
end
```

- With this padding, center of `Ppad` = center of `P`

Creating Blurred Image

If we are *given* blurred image data:

- We try to make a best guess at what boundary condition is most realistic.
- Construct **A** using this boundary condition.

If we are *creating* blurred image data:

- We should simulate actual boundaries of an infinite scene.
- This can be done by blurring a large “true” image scene.
- Then extract the central part of the image.

Creating Blurred Image: Matlab example

```
Xbig = double(imread('iograyBorder.tif'));  
[P, center] = psfGauss([512,512], s);  
Pbig = padPSF(P, size(Xbig));  
Sbig = fft2(circshift(Pbig, 1-center));  
Bbig = real(ifft2(Sbig .* fft2(Xbig)));  
X = Xbig(51:562,51:562);  
B = Bbig(51:562,51:562);
```

Use P, center, B, X as realistic (noise free) test data.

Additive Noise

Additive noise \Rightarrow add random perturbations to blurred image.

- Use Matlab `randn` function.
- Scale perturbations to data.
- Add to blurred image.

For example,

```
E = randn(size(B));  
E = E / norm(E(:));  
B = B + 0.01*norm(B(:))*E;
```

generates “1% noise.”