For students of HI 5323
"Image Processing"

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http://biomachina.org/courses/processing/05.html

## Interpolation

## Forward Mapping

Let $u(x, y)$ and $v(x, y)$ be a mapping from location $(x, y)$ to $(u, v)$ :

$$
B[u(x, y), v(x, y)]=A[x, y]
$$



## Forward Mapping: Problems

- Doesn't always map to pixel locations
- Solution: spread out effect of each pixel, e.g. by bilinear interpolation



## Forward Mapping: Problems

- May produce holes in the output



## Forward Mapping: Problems

- May produce holes in the output
- Solution: sample source image ( $A$ ) more often
- Still can leave holes



## Backward Mapping

Let $x(u, v)$ and $y(u, v)$ be an inverse mapping from location $(x, y)$ to $(u, v)$ :

$$
B[u, v]=A[x(u, v), y(u, v)]
$$



## Backward Mapping: Problems

- Doesn't always map from a pixel
- Solution: Interpolate between pixels



## Backward Mapping: Problems

- May produce holes in the input
- Solution: reduce input image (by averaging pixels) and sample reduced/averaged image $\rightarrow$ MIP-maps



## Interpolation

- "Filling In" between the pixels
- A function of the neighbors or a larger neighborhood
- Methods:
- Nearest neighbor
- Bilinear
- Bicubic or other higher-order


## Interpolation: Nearest-Neighbor

- Simplest to implement: the output pixel is assigned the value of the pixel that the point falls within
- Round off $x$ and $y$ values to nearest pixel
- Result is not continuous (blocky)



## Interpolation: Linear (1D)

- General idea:
original function values



## To calculate the interpolated values



$$
\frac{F-f\left(x_{1}\right)}{\lambda}=\frac{f\left(x_{2}\right)-f\left(x_{1}\right)}{1}
$$

## Interpolation: Linear (2D)

- How a $4 \times 4$ image would be interpolated to produce an $8 \times 8$ image?



## Bilinear Interpolation

- Substituting with the values just obtained:

$$
\begin{aligned}
f\left(x^{\prime}, y^{\prime}\right) & =\lambda(\mu f(x+1, y+1)+(1-\mu) f(x+1, y)) \\
& +(1-\lambda)(\mu f(x, y+1)+(1-\mu) f(x, y))
\end{aligned}
$$

- You can do the expansion as an exercise.
- This is the formulation for bilinear interpolation


## Bilinear Interpolation

- The output pixel value is a weighted average of pixels in the nearest 2-by-2 neighborhood
- Linearly interpolate in one direction (e.g., vertically)
- Linearly interpolate results in the other direction (horizontally)



## General Interpolation

- We wish to interpolate a value $\mathrm{f}\left(\mathrm{x}^{\prime}\right)$ for $x_{1} \leq x^{\prime} \leq x_{2}$ and suppose $x^{\prime}-x_{1}=\lambda$
- We define an interpolation kernel $\mathrm{R}(\mathrm{u})$ and set

$$
f\left(x^{\prime}\right)=R(-\lambda) f\left(x_{1}\right)+R(1-\lambda) f\left(x_{2}\right)
$$



## General Interpolation: $0^{\text {th }}$ and $1^{\text {st }}$ orders

- Consider 2 functions $R_{0}(u)$ and $R_{1}(u)$

$R_{0}(u)=\left\{\begin{array}{lr}0 & \text { if } u \leq-0.5 \\ 1 & \text { if }-0.5<u \leq 0.5 \\ 0 & \text { if } u>0.5\end{array} \quad R_{1}(u)= \begin{cases}1+u & \text { if } u \leq 0 \\ 1-u & \text { if } u \geq 0\end{cases}\right.$
Substitute $R_{0}(u)$ for $R(u) ~ \square$ nearest-neighbor interpolation.
Substitute $R_{1}(u)$ for $R(u) ~ l i n e a r$ interpolation.


## Interpolation Kernel



## Interpolation Kernel



## Interpolation Kernel



## Interpolation Kernel



## Interpolation Kernel



## Interpolation Kernel



## Interpolation Kernel



## Interpolation Kernel



## Interpolation Kernel



## Interpolation Kernel



## Interpolation Kernel



## Interpolation Kernel



## Interpolation Kernel



## Interpolation Kernel



## Interpolation Kernel



## 1D Interpolation

Zero Order
Nearest Neighbor


## 1D Interpolation

## Zero Order

Nearest Neighbor


## 1D Interpolation

## Zero Order

Nearest Neighbor


## 1D Interpolation

Zero Order
Nearest Neighbor


## 1D Interpolation

First Order
Linear Interpolation


## 1D Interpolation

First Order
Linear Interpolation


## 1D Interpolation

First Order
Linear Interpolation


## 1D Interpolation

First Order
Linear Interpolator


## 1D Interpolation

Second Order
Quadratic Interpolation


## 1D Interpolation

Second Order
Quadratic Interpolation


## 1D Interpolation

Second Order
Quadratic Interpolation


## 1D Interpolation

## Second Order

Quadratic Interpolator


## 1D Interpolation

Third Order
Cubic Interpolation


## 1D Interpolation

Third Order
Cubic Interpolation


## 1D Interpolation

Third Order
Cubic Interpolation


## 1D Interpolation

Third Order
Cubic Interpolation


## Remarks About Higher-Order Interpolation

- Higher-degree polynomials:
- e.g., cubic
- Sometimes other interpolating functions
- Requires a larger neighborhood:
- e.g., bicubic requires a $4 \times 4$ neighborhood
- More expensive


## Another $3^{\text {rd }}$ order (Cubic) Example

$$
R_{3}(u)=\left\{\begin{array}{cc}
1.5|u|^{3}-2.5|u|^{2}+1 & \text { if }|u| \leq 1 \\
-0.5|u|^{3}+2.5|u|^{2}-4|u|+2 & \text { if } 1<|u| \leq 2
\end{array}\right.
$$



Now have 4 support points:

$$
f\left(x^{\prime}\right)=R_{3}(-1-\lambda) f\left(x_{1}\right)+R_{3}(-\lambda) f\left(x_{2}\right)+R_{3}(1-\lambda) f\left(x_{3}\right)+R_{3}(2-\lambda) f\left(x_{4}\right)
$$

## 2D Interpolation

## Kernel Product



## 2D Interpolation

## Kernel Product



## 2D Interpolation

Kernel Product

## x, y separable variables



## Bicubic (2D)

- Bicubic interpolation fits a series of cubic polynomials to the brightness values contained in the $4 \times 4$ array of pixels surrounding the calculated address.
- Step 1: four cubic polynomials $F(i), i=0,1,2,3$ are fit to the control points along the rows. The fractional part of the calculated pixel's address in the $x$-direction is used.



## Bicubic (2D)

- Step 2: the fractional part of the calculated pixel's address in the y-direction is used to fit another cubic polynomial down the column, based on the interpolated brightness values that lie on the curves $F(i), i=0, \ldots, 3$.



## Bicubic (2D)

- Substituting the fractional part of the calculated pixel's address in the x -direction into the resulting cubic polynomial then yields the interpolated pixel's brightness value.



## Three Interpolations Comparison

- Trade offs:
- Aliasing versus blurring
- Computation speed

nearest neighbor

bilinear

bicubic


## General Interpolation: Summary

- For NN interpolation, the output pixel is assigned the value of the pixel that the point falls within. No other pixels are considered.
- For bilinear interpolation, the output pixel value is a weighted average of pixels in the nearest 2-by-2 neighborhood.
- For bicubic interpolation, the output pixel value is a weighted average of pixels in the nearest 4-by-4 neighborhood.
- Bilinear method takes longer than nearest neighbor interpolation, and the bicubic method takes longer than bilinear.
- The greater the number of pixels considered, the more accurate the computation is, so there is a trade-off between processing time and quality.
- Only trade-off of higher order methods is edge-preservation.
- Sometimes hybrid methods are used.


## 2D Geometric Operations

## 2D Geometric Operations: Translation

Shifting left-right and/or up-down:

$$
\begin{aligned}
& x^{\prime}=x+x_{0} \\
& y^{\prime}=y+y_{0}
\end{aligned}
$$

Matrix form:


$$
\left[\begin{array}{c}
x^{\prime} \\
y^{\prime} \\
1
\end{array}\right]=\left[\begin{array}{llc}
1 & 0 & x_{0} \\
0 & 1 & y_{0} \\
0 & 0 & 1
\end{array}\right]\left[\begin{array}{l}
x \\
y \\
1
\end{array}\right]=\left[\begin{array}{c}
x+x_{0} \\
y+y_{0} \\
1
\end{array}\right]
$$

Convenient Notation: Homogeneous Coordinates

- Add one dimension, treat transformations as matrix multiplication
- Can be generalized to 3D


## 2D Geometric Operations: Reflection

Reflection Y

$$
\left[\begin{array}{c}
t_{x}^{\prime} \\
t_{y}^{\prime} \\
1
\end{array}\right]=\left[\begin{array}{ccc}
1 & 0 & 0 \\
0 & -1 & 0 \\
0 & 0 & 1
\end{array}\right] \cdot\left[\begin{array}{c}
t_{x} \\
t_{y} \\
1
\end{array}\right]
$$



Reflection X

$$
\left[\begin{array}{c}
t_{x}^{\prime} \\
t_{y}^{\prime} \\
1
\end{array}\right]=\left[\begin{array}{ccc}
-1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{array}\right] \cdot\left[\begin{array}{c}
t_{x} \\
t_{y} \\
1
\end{array}\right]
$$



## 2D Geometric Operations: Scaling

Enlarging or reducing horizontally and/or vertically:

$$
\begin{aligned}
& x^{\prime}=S_{x} x \\
& y^{\prime}=S_{y} y
\end{aligned}
$$

Matrix form:

$$
\left[\begin{array}{c}
x^{\prime} \\
y^{\prime} \\
1
\end{array}\right]=\left[\begin{array}{ccc}
S_{x} & 0 & 0 \\
0 & S_{y} & 0 \\
0 & 0 & 1
\end{array}\right]\left[\begin{array}{l}
x \\
y \\
1
\end{array}\right]=\left[\begin{array}{c}
S_{x} x \\
S_{y} y \\
1
\end{array}\right]
$$

## 2D Geometric Operations: Rotation

Result components dependent on both $x \& y$ :

$$
\begin{aligned}
& x^{\prime}=\cos (\theta) x-\sin (\theta) y \\
& y^{\prime}=\sin (\theta) x+\cos (\theta) y
\end{aligned}
$$

Matrix form:


$$
\left[\begin{array}{c}
x^{\prime} \\
y^{\prime} \\
1
\end{array}\right]=\left[\begin{array}{ccc}
\cos (\theta) & -\sin (\theta) & 0 \\
\sin (\theta) & \cos (\theta) & 0 \\
0 & 0 & 1
\end{array}\right]\left[\begin{array}{l}
x \\
y \\
1
\end{array}\right]=\left[\begin{array}{c}
\cos (\theta) x-\sin (\theta) y \\
\sin (\theta) x+\cos (\theta) y \\
1
\end{array}\right]
$$

## Rotation Operation: Problems

- In image space, when rotating a collection of points, what could go wrong?



## Rotation Operation: Problems

- Problem1: part of rotated image might fall out of valid image range.
- Problem2: how to obtain the intensity values in the rotated image?


Consider all integer-valued points ( $x^{\prime}, y^{\prime}$ ) in the dashed rectangle.
A point will be in the image if, when rotated back, it lies within the original image limits.

$$
0 \leq x^{\prime} \cos \theta+y^{\prime} \sin \theta \leq a
$$

$0 \leq-x^{\prime} \sin \theta+y^{\prime} \cos \theta \leq b$

See homework assignment 2!

## 2D Geometric Operations: Affine Transforms

Linear combinations of $x, y$, and 1 : encompasses all translation, scaling, \& rotation (also skew and shear):

$$
\begin{aligned}
& x^{\prime}=a x+b y+c \\
& y^{\prime}=d x+e y+f
\end{aligned}
$$

Matrix form:

$$
\left[\begin{array}{l}
x^{\prime} \\
y^{\prime} \\
1
\end{array}\right]=\left[\begin{array}{lll}
a & b & c \\
d & e & f \\
0 & 0 & 1
\end{array}\right]\left[\begin{array}{l}
x \\
y \\
1
\end{array}\right]=\left[\begin{array}{c}
a x+b y+c \\
d x+e y+f \\
1
\end{array}\right]
$$

## Affine Transformations (cont.)

- Translations and rotations are rigid body transformations
- General affine transformations also include non-rigid transformations (e.g., skew or shear)
- Affine means that parallel lines transform to parallel lines



## Compound Transformations

Example: rotation around the point $\left(x_{0}, y_{0}\right)$

$$
\left[\begin{array}{ccc}
1 & 0 & x_{0} \\
0 & 1 & y_{0} \\
0 & 0 & 1
\end{array}\right]\left[\begin{array}{ccc}
\cos (\theta) & -\sin (\theta) & 0 \\
\sin (\theta) & \cos (\theta) & 0 \\
0 & 0 & 1
\end{array}\right]\left[\begin{array}{ccc}
1 & 0 & -x_{0} \\
0 & 1 & -y_{0} \\
0 & 0 & 1
\end{array}\right]\left[\begin{array}{l}
x \\
y \\
1
\end{array}\right]
$$

Matrix multiplication is associative (but not commutative):

$$
B(A v)=(B A) v=C v
$$

where $C=B A$

- Can compose multiple transformations into a single matrix
- Much faster when applying same transform to many pixels


## Compound Transformations

## Example:



## Inverting Matrix Transformations

If

$$
v^{\prime}=M v
$$

then

$$
v=M^{-1} v^{\prime}
$$

Thus, to invert the transformation, invert the matrix
Useful for computing the backward mapping given the forward transform

For more info see e.g.
http://home.earthlink.net/~jimlux/radio/math/matinv.htm

## Morphing: Deformations in 2D and 3D

## Morphing: Deformations in 2D and 3D

- Parametric Deformations
- Cross-Dissolve
- Mesh Warping
- Control Points


## Parametric Deformations

## Parametric Deformations - Taper



$$
\begin{array}{cc}
x^{\prime}=x \\
y^{\prime}=f(x) & {\left[\begin{array}{l}
x^{\prime} \\
y^{\prime}
\end{array}\right]=\left[\begin{array}{cc}
1 & 0 \\
0 & f(x)
\end{array}\right] \cdot\left[\begin{array}{l}
x \\
y
\end{array}\right]} \\
& P^{\prime}=M(P) \cdot P
\end{array}
$$

b) tapered object

## Parametric Deformations - Taper



## Parametric Deformations - Twist

$$
\begin{aligned}
& x^{\prime}=s(z) \cdot x \\
& y^{\prime}=s(z) \cdot y \\
& z^{\prime}=z
\end{aligned}
$$

$$
\text { Where } \mathrm{s}(\mathrm{z})=\frac{(\max z-\mathrm{z})}{(\max z-\min z)}
$$

## Parametric Deformations - Twist



## Parametric Deformations - Bend

| $y_{0}-c e n t e r ~ o f ~ b e n d ~$ |
| :--- |
| $1 / k-r a d i u s ~ o f ~ b e n d ~$ |
| $y_{\text {mim }} y_{\text {max }}$ - hend region |

$$
y=\begin{array}{cc}
y_{\text {min }} & y \leq y_{\text {win }} \\
y & y_{\text {min }}<y<y_{\text {max }} \\
y_{\text {mux }} & y \geq y_{\text {mux }}
\end{array}
$$

$$
\begin{gathered}
\theta=k \cdot\left(y-y_{0}\right) \\
C_{\theta}=\cos \theta \\
s_{\theta}=\sin \theta
\end{gathered}
$$

$$
x^{\prime} \equiv x
$$

$$
y^{\prime}=\left(\begin{array}{l}
-S_{0} \cdot z-\frac{1}{k}+y_{0} \\
-\left(S_{0} \cdot\left(z-\frac{1}{k}\right)\right)+y_{0}+C_{0} \cdot\left(y-y_{v i n}\right) \\
\left(-\left(S_{0} \cdot\left(z-\frac{1}{k}\right)\right)+y_{0}+C_{0} \cdot\left(y-y_{\max }\right)\right.
\end{array}\right.
$$

$$
y_{\text {mix }} \leq y \leq y_{\operatorname{six} x}
$$

$$
y<y_{\mathrm{vin}}
$$

$$
y>y_{\max }
$$

$$
z^{\prime}=\left(\begin{array}{l}
-C_{\theta} \cdot z-\frac{1}{k}+\frac{1}{k} \\
-\left(C_{\theta} \cdot\left(z-\frac{1}{k}\right)\right)+\frac{1}{k}+S_{0} \cdot\left(y-y_{\text {nula }}\right) \\
\left(-\left(C_{\theta} \cdot\left(z-\frac{1}{k}\right)\right)+\frac{1}{k}+S_{\theta} \cdot\left(y-y_{s u \Delta x}\right)\right.
\end{array}\right.
$$

$$
\begin{gathered}
y_{\text {min }} \leq y \leq y_{\text {max }} \\
y<y_{\text {min }} \\
y>y_{\text {mas }}
\end{gathered}
$$

## Parametric Deformations - Bend




## Parametric Deformations - Compound


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## Image Blending

## Image Blending

- Goal is smooth transformation between image of one object and another
- The idea is to get a sequence of intermediate images which when put together with the original images would represent the change from one image to the other
- Realized by
- Image warping
- Color blending
- Image blending has been widely used in creating movies, music videos and television commercials
- Terminator 2


## Cross-Dissolve (Cross-Fading)

- Simplest approach is cross-dissolve:
- linear interpolation to fade from one image (or volume) to another
- No geometrical alignment between images (or volumes)
- Pixel-by-pixel (or voxel by voxel) interpolation
- No smooth transitions, intermediate states not realistic



## Problems

- Problem with cross-dissolve is that if features don't line up exactly, we get a double image
- Can try shifting/scaling/etc. one entire image to get better alignment, but this doesn't always fix problem
- Can handle more situations by applying different warps to different pieces of image
- Manually chosen
- Takes care of feature correspondences


Image $\mathbf{I}_{\mathrm{S}}$ with mesh $\quad$ Image $\mathbf{I}_{\mathrm{T}}$, mesh $\mathbf{M}_{\mathrm{T}}$ $\mathbf{M}_{S}$ defining pieces

Mesh Warping

## Mesh Warping Application

Images $I_{S}$ \& meshes Ms

from G. Wolberg, CGI ‘96

## Mesh Warping



## Mesh Warping



## Mesh Warping

- Source and target images are meshed
- The meshes for both images are interpolated
- The intermediate images are cross-dissolved
- Here, we look at 2D example


## Mesh Warping Algorithm

- Algorithm
for each frame $f$ do
- interpolate mesh M , between $\mathrm{M}_{\mathrm{s}}$ and $\mathrm{M}_{\mathrm{t}}$
- warp Image $I_{s}$ to $I_{1}$, using meshes $M_{s}$ and $M$
- warp Image $I_{t}$ to $I_{2}$, using meshes $M_{t}$ and $M$
- interpolate image $\mathrm{I}_{1}$ and $\mathrm{I}_{2}$
end
$-I_{s}$ : source image, $I_{t}:$ target image
- source image has mesh $M_{s}$, target image has mesh $M_{t}$


## Mesh Deformation



## Mesh Deformation



## Mesh Deformation



## Mesh Deformation



For each vertex identify cell, fractional u,v coordinate in unit cell

## Mesh Deformation



## Mesh Deformation



## Mesh Deformation



## Free-Form Deformations



## FFD - Register Point in Cell



## FFD - Register Point in Cell



## FFD - Create Control Grid


(not necessarily orthogonal)

## FFD - Move and Reposition

Move control grid points


Usually tri-cubic interpolation is used with FFDs

Originally, Bezier interpolation was used.
B-spline and Catmull-Romm interpolation have also been used (as well as tri-linear interpolation)

## FFD Example

Step1


It is originally a cylinder.
Red boundary is FFD block embedded with that cylinder.


Move control points of each end, and you can see cylinder inside also changes.

## FFD Example

step3


Move inner control points downwards.
step4


Finally, get a shaded version of banana!

## BSplines (Cubic) Interpolation



Original Lena

## BSplines (Cubic) Interpolation



Deformed with BSpline Transform

## Deformable Registration Framework



## Deformable Registration



Deformed with BSpline Transform

## Deformable Registration



Registered with BSpline Transform

## Deformable Registration



Original Lena

## Deformable Registration



Difference Before Registration

Difference After Registration

## Control Point Warping

## Control Point Warping

Instead of a warping mesh, use arbitrary correspondence points:
Tip of one person's nose to the tip of another, eyes to eyes, etc.

Interpolate between correspondence points to determine how points move
Apply standard warping (forward or backward):
In-between image is a weighted average of the source and destination corresponding pixels
Here we look at 3D example...

## Finding Control Points in 3D Structures



Actin filament: Reconstruction from EM data at $20 \AA$ resolution

rmsd: $1.1 \AA$

## Control Point Displacements

Have 2 conformations, both source and target characterized by control points


RNA Polymerase, Wriggers, Structure, 2004, Vol. 12, pp. 1-2.

## Piecewise-Linear Inter- / Extrapolation

For each probe position find 4 closest control points.
Ansatz: $\quad F_{x}(x, y, z)=a x+b y+c z+d$

$$
\begin{aligned}
& F_{x}\left(\mathbf{w}_{1}\right)=f_{1, x}, \\
& F_{x}\left(\mathbf{w}_{2}\right)=f_{2, x}, \\
& F_{x}\left(\mathbf{w}_{3}\right)=f_{3, x}, \\
& F_{x}\left(\mathbf{w}_{4}\right)=f_{4, x} \quad\left(\text { similar for } F_{y}, F_{z}\right) .
\end{aligned}
$$



Cramer's rule:
$a=\frac{\left|\begin{array}{llll}f_{1, x} & w_{1, y} & w_{1, z} & 1 \\ f_{2, x} & w_{2, y} & w_{2, z} & 1 \\ f_{3, x} & w_{3, y} & w_{3, z} & 1 \\ f_{4, x} & w_{4, y} & w_{4, z} & 1\end{array}\right|}{D}, b=\frac{\left|\begin{array}{llll}w_{1, x} & f_{1, y} & w_{1, z} & 1 \\ w_{2, x} & f_{2, y} & w_{2, z} & 1 \\ w_{3, x} & f_{3, y} & w_{3, z} & 1 \\ w_{4, x} & f_{4, y} & w_{4, z} & 1\end{array}\right|}{D}, \cdots, \quad D=\left|\begin{array}{llll}w_{1, x} & w_{1, y} & w_{1, z} & 1 \\ w_{2, x} & w_{2, y} & w_{2, z} & 1 \\ w_{3, x} & w_{3, y} & w_{3, z} & 1 \\ w_{4, x} & w_{4, y} & w_{4, z} & 1\end{array}\right|$
See e.g. http://mathworld.wolfram.com/CramersRule.html

## Non-Linear Kernel Interpolation

Consider all $k$ control points and interpolation kernel function $U(r)$.
Ansatz:

$$
\begin{aligned}
& F_{x}(x, y, z)=a_{1}+a_{x} x+a_{y} y+a_{z} z+\sum_{k=1}^{k} b_{i} \cdot U\left(\left|\mathbf{w}_{i}-(x, y, z)\right|\right) \\
& F_{x}\left(\mathbf{w}_{i}\right)=f_{i, x}, \forall i \quad\left(\text { similar for } F_{y}, F_{z}\right) .
\end{aligned}
$$

Solve :

$$
\begin{aligned}
& \mathrm{L}^{-1}\left(f_{1, x}, \cdots, f_{k, x}, 0,0,0,0\right)=\left(b_{1}, \cdots, b_{k}, a_{1}, a_{x}, a_{y}, a_{z}\right)^{\mathrm{T}}, \\
& \text { where } \quad \mathbf{L}=\left(\begin{array}{c|c}
\mathbf{P} & \mathbf{Q} \\
\hline \mathbf{Q}^{\mathrm{T}} & \mathbf{0}
\end{array}\right), \quad \mathbf{Q}=\left(\begin{array}{cccc}
1 & w_{1, x} & w_{1, y} & w_{1, z} \\
\cdots & \cdots & \cdots & \cdots \\
1 & w_{k, x} & w_{k, y} & w_{k, z}
\end{array}\right), k \times 4, \\
& \mathbf{P}=\left(\begin{array}{cccc}
0 & U\left(w_{12}\right) & \cdots & U\left(w_{1 k}\right) \\
U\left(w_{21}\right) & 0 & \cdots & U\left(w_{2 k}\right) \\
\cdots & \cdots & \cdots & \cdots \\
U\left(w_{k 1}\right) & U\left(w_{k 2}\right) & \cdots & 0
\end{array}\right), k \times k .
\end{aligned}
$$

## Bookstein "Thin-Plate" Splines

- kernel function $U(r)$ is principal solution of biharmonic equation that arises in elasticity theory of thin plates:

$$
\Delta^{2} U(r)=\nabla^{4} U(r)=\delta(r)
$$

- variational principle: $U(r)$ minimizes the bending energy (not shown).
-1D: $U(r)=\left|r^{3}\right|$ (cubic spline)
-2D: $U(r)=r^{2} \log r^{2}$
-3D: $U(r)=|r|$



## RNAP Example: Source Structure



## Piecewise-Linear Inter- / Extrapolation



## Thin-Plate Splines, 3D $|\mathrm{r}|$ Kernel



## Control: Molecular Dynamics



## Resources

Textbooks:
Kenneth R. Castleman, Digital Image Processing, Chapter 8 John C. Russ, The Image Processing Handbook, Chapter 3

Online Graphics Animations: http://nis-lab.is.s.u-tokyo.ac.jp/~nis/animation.html

