Sampling and reconstruction

CS 4620

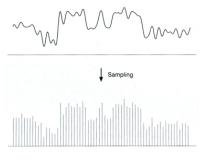
Shirley and Marschner, 3rd ed Chapter 9 "Signal Processing"

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Sampled representations

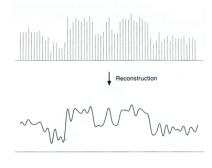
- How to store and compute with continuous functions?
- Common scheme for representation: samples write down the function's values at many points



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Reconstruction

 Making samples back into a continuous function for output (need realizable method)
 for analysis or processing (need mathematical method)
 amounts to "guessing" what the function did in between



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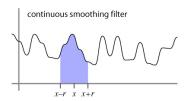
[FvDfH fig.14.14b / Wolberg]

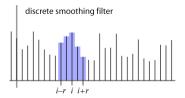
[FvDFH fig.14.14b / Wolbe

Filtering

- Processing done on a function

 can be executed in continuous form (e.g. analog circuit)
 but can also be executed using sampled representation
- · Simple example: smoothing by averaging

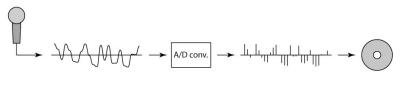




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Sampling in digital audio

- Recording: sound to analog to samples to disc
- Playback: disc to samples to analog to sound again how can we be sure we are filling in the gaps correctly?





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Roots of sampling

 Nyquist 1928; Shannon 1949 famous results in information theory

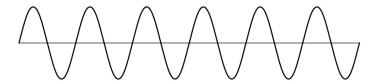
- 1940s: first practical uses in telecommunications
- 1960s: first digital audio systems
- 1970s: commercialization of digital audio
- 1982: introduction of the Compact Disc the first high-profile consumer application
- This is why all the terminology has a communications or audio "flavor"

early applications are 1D; for us 2D (images) is important

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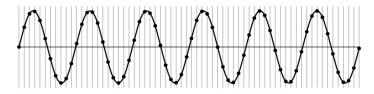
Undersampling

- · What if we "missed" things between the samples?
- Simple example: undersampling a sine wave unsurprising result: information is lost surprising result: indistinguishable from lower frequency also was always indistinguishable from higher frequencies aliasing: signals "traveling in disguise" as other frequencies



Undersampling

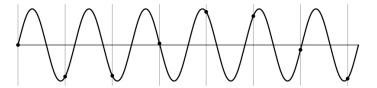
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Undersampling

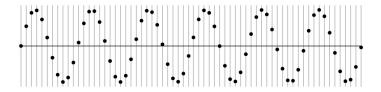
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Undersampling

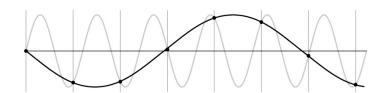
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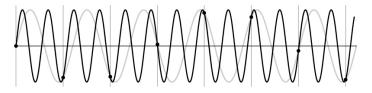
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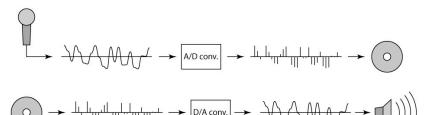
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Preventing aliasing

• Introduce lowpass filters:

remove high frequencies leaving only safe, low frequencies choose lowest frequency in reconstruction (disambiguate)

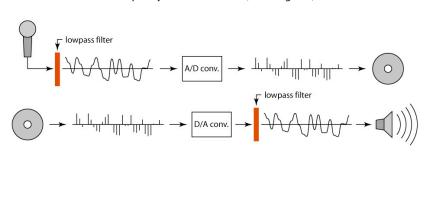


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Preventing aliasing

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remove high frequencies leaving only safe, low frequencies choose lowest frequency in reconstruction (disambiguate)



Linear filtering: a key idea

• Transformations on signals; e.g.:

bass/treble controls on stereo blurring/sharpening operations in image editing smoothing/noise reduction in tracking

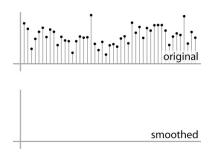
Key properties

linearity: filter(f + g) = filter(f) + filter(g) shift invariance: behavior invariant to shifting the input

- · delaying an audio signal
- · sliding an image around
- Can be modeled mathematically by convolution

Convolution warm-up

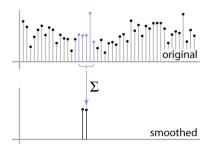
- basic idea: define a new function by averaging over a sliding window
- a simple example to start off: smoothing



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Convolution warm-up

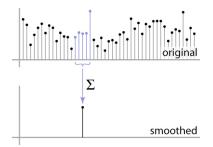
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Convolution warm-up

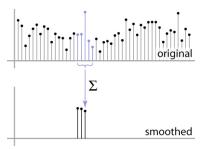
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Convolution warm-up

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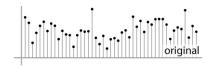


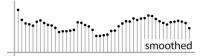
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Convolution warm-up

- basic idea: define a new function by averaging over a sliding window
- a simple example to start off: smoothing





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Discrete convolution

• Simple averaging:

$$b_{\text{smooth}}[i] = \frac{1}{2r+1} \sum_{j=i-r}^{i+r} b[j]$$

every sample gets the same weight

• Convolution: same idea but with weighted average

$$(a \star b)[i] = \sum_{j} a[j]b[i-j]$$

each sample gets its own weight (normally zero far away)

• This is all convolution is: it is a moving weighted average

Convolution warm-up

• Same moving average operation, expressed mathematically:

$$b_{\text{smooth}}[i] = \frac{1}{2r+1} \sum_{j=i-r}^{i+r} b[j]$$

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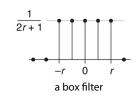
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Filters

- Sequence of weights a[j] is called a filter
- Filter is nonzero over its region of support usually centered on zero: support radius r
- Filter is normalized so that it sums to 1.0 this makes for a weighted average, not just any old weighted sum
- Most filters are symmetric about 0 since for images we usually want to treat left and right the same

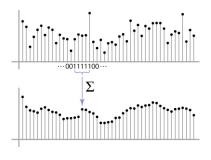


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Convolution and filtering

- Can express sliding average as convolution with a box filter
- $a_{box} = [..., 0, 1, 1, 1, 1, 1, 0, ...]$



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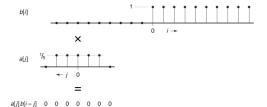
Example: box and step

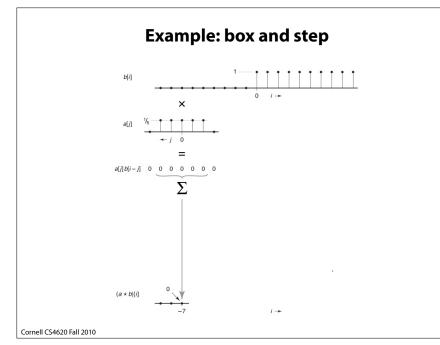


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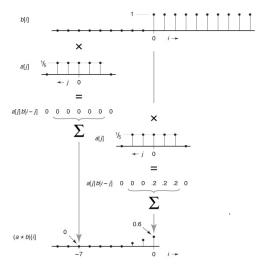
Example: box and step

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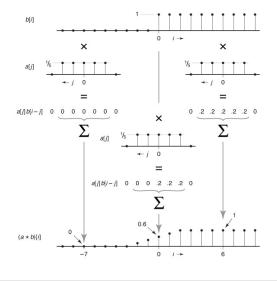




Example: box and step

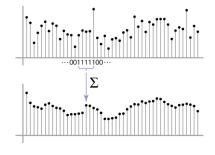


Example: box and step



Convolution and filtering

- Convolution applies with any sequence of weights
- Example: Bell curve (Gaussian-like) [..., 1, 4, 6, 4, 1, ...]/16

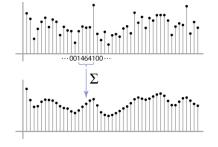


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Convolution and filtering

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And in pseudocode...

 $\begin{aligned} & \textbf{function} \text{ convolve}(\text{sequence } a, \text{ sequence } b, \text{ int } r, \text{ int } i \text{ }) \\ & s = 0 \\ & \textbf{for } j = -r \text{ to } r \\ & s = s + a[j]b[i-j] \\ & \textbf{return } s \end{aligned}$

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Discrete filtering in 2D

• Same equation, one more index

$$(a \star b)[i, j] = \sum_{i', j'} a[i', j']b[i - i', j - j']$$

now the filter is a rectangle you slide around over a grid of numbers

- Commonly applied to images blurring (using box, using gaussian, ...)
 sharpening (impulse minus blur)
- Usefulness of associativity often apply several filters one after another: $(((a*b_1)*b_2)*b_3)$ this is equivalent to applying one filter: $a*(b_1*b_2*b_3)$

Discrete convolution

• Notation: $b = c \star a$

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• Convolution is a multiplication-like operation commutative $a\star b=b\star a$ associative $a\star (b\star c)=(a\star b)\star c$ distributes over addition $a\star (b+c)=a\star b+a\star c$ scalars factor out $\alpha a\star b=a\star \alpha b=\alpha (a\star b)$ identity: unit impulse $\mathbf{e}=[...,0,0,1,0,0,...]$ $a\star e=a$

• Conceptually no distinction between filter and signal

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And in pseudocode...

```
function convolve2d(filter2d a, filter2d b, int i, int j) s=0 r=a.radius for i'=-r to r do for j'=-r to r do s=s+a[i'][j']b[i-i'][j-j'] return s
```

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Optimization: separable filters

- basic alg. is $O(r^2)$: large filters get expensive fast!
- definition: $a_2(x,y)$ is separable if it can be written as:

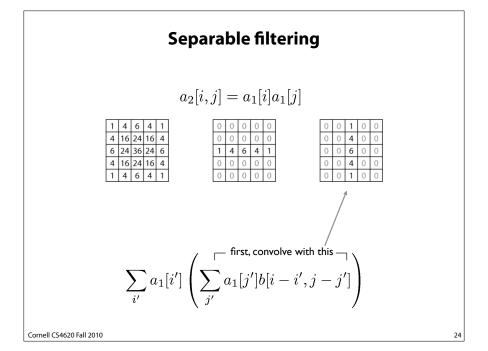
$$a_2[i,j] = a_1[i]a_1[j]$$

this is a useful property for filters because it allows factoring:

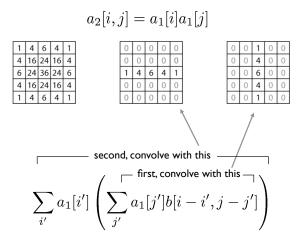
$$(a_2 \star b)[i,j] = \sum_{i'} \sum_{j'} a_2[i',j']b[i-i',j-j']$$

$$= \sum_{i'} \sum_{j'} a_1[i']a_1[j']b[i-i',j-j']$$

$$= \sum_{i'} a_1[i'] \left(\sum_{j'} a_1[j']b[i-i',j-j']\right)$$



Separable filtering

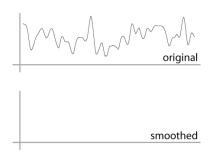


Continuous convolution: warm-up

 Can apply sliding-window average to a continuous function just as well

output is continuous

integration replaces summation



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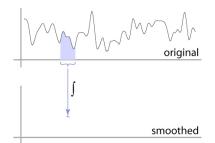
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Continuous convolution: warm-up

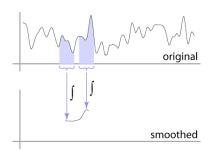
 Can apply sliding-window average to a continuous function just as well

output is continuous

24

25

integration replaces summation



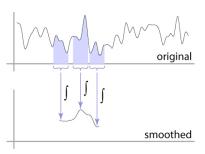
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Continuous convolution: warm-up

 Can apply sliding-window average to a continuous function just as well

output is continuous integration replaces summation



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Continuous convolution

• Sliding average expressed mathematically:

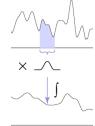
$$g_{\text{smooth}}(x) = \frac{1}{2r} \int_{x-r}^{x+r} g(t)dt$$

note difference in normalization (only for box)

· Convolution just adds weights

$$(f \star g)(x) = \int_{-\infty}^{\infty} f(t)g(x-t)dt$$

weighting is now by a function weighted integral is like weighted average again bounds are set by support of f(x)

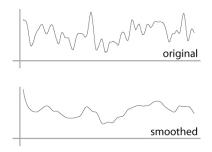


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25

25

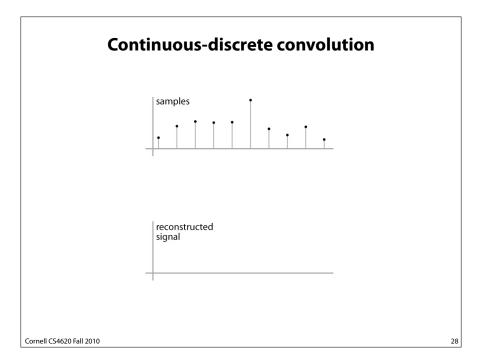
27

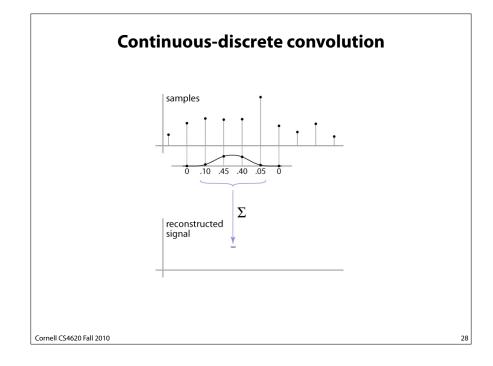
One more convolution

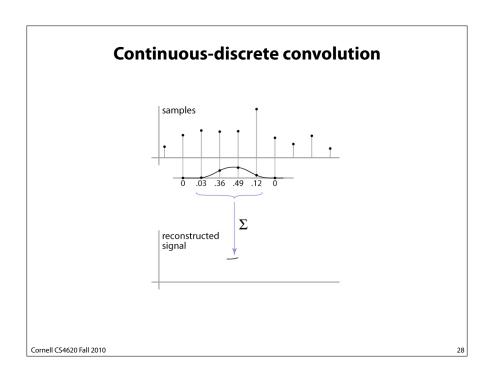
Continuous–discrete convolution

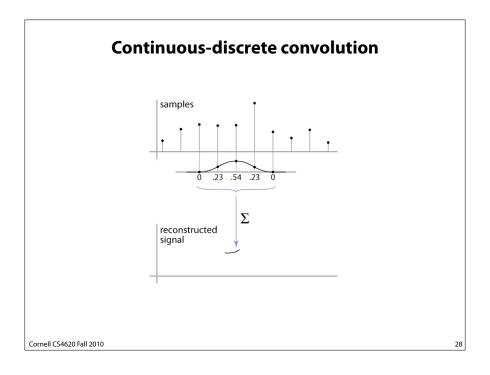
$$(a \star f)(x) = \sum_{i} a[i]f(x-i)$$
$$(a \star f)(x,y) = \sum_{i,j} a[i,j]f(x-i,y-j)$$

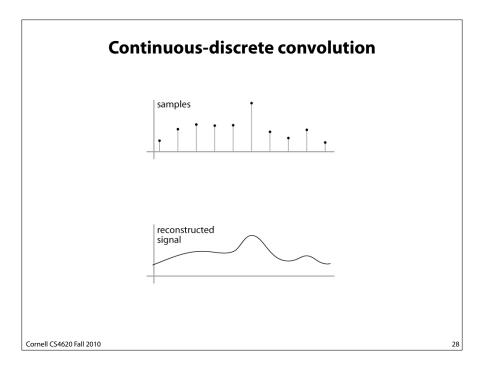
used for reconstruction and resampling











Resampling

- Changing the sample rate
 in images, this is enlarging and reducing
- Creating more samples:

increasing the sample rate "upsampling"

"enlarging"

• Ending up with fewer samples:

decreasing the sample rate

"downsampling"

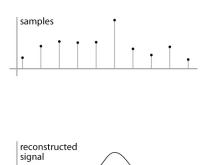
"reducing"

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Resampling

• Reconstruction creates a continuous function forget its origins, go ahead and sample it

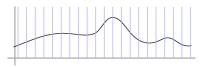


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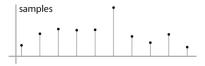


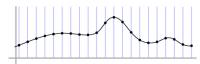
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Resampling

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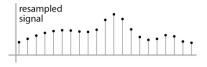
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Resampling

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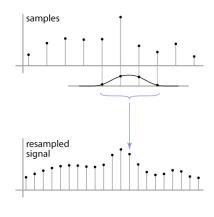
30

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30

Resampling

• Reconstruction creates a continuous function forget its origins, go ahead and sample it



And in pseudocode...

function reconstruct(sequence a, filter f, real x)

$$s = 0$$

$$r = f$$
.radius

for
$$i = \lceil x - r \rceil$$
 to $\lfloor x + r \rfloor$ **do** $s = s + a[i]f(x - i)$

return s

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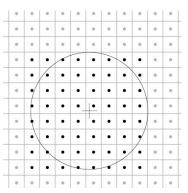
Cont.-disc. convolution in 2D

· same convolution—just two variables now

$$(a \star f)(x,y) = \sum_{i,j} a[i,j]f(x-i,y-j)$$

loop over nearby pixels, average using filter weight looks like discrete filter, but offsets are not integers and filter is continuous

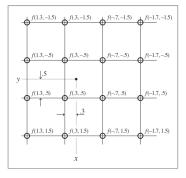
remember placement of filter relative to grid is variable



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Cont.-disc. convolution in 2D

$$(a \star f)(x, y) = \sum_{i,j} a[i, j] f(x - i, y - j)$$



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Separable filters for resampling

• just as in filtering, separable filters are useful

separability in this context is a statement about a continuous filter, rather than a discrete one:

$$f_2(x,y) = f_1(x)f_1(y)$$

- resample in two passes, one resampling each row and one resampling each column
- intermediate storage required: product of one dimension of src. and the other dimension of dest.
- · same yucky details about boundary conditions

two-stage resampling using a separable filter

A gallery of filters

Box filter

Simple and cheap

Tent filter

Linear interpolation

Gaussian filter

Very smooth antialiasing filter

• B-spline cubic

Very smooth

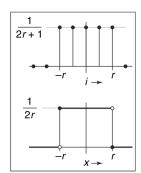
- Catmull-rom cubic Interpolating
- Mitchell-Netravali cubic
 Good for image upsampling

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Box filter

$$a_{\mathrm{box},r}[i] = \begin{cases} 1/(2r+1) & |i| \leq r, \\ 0 & \text{otherwise.} \end{cases}$$

$$f_{\text{box},r}(x) = \begin{cases} 1/(2r) & -r \le x < r, \\ 0 & \text{otherwise.} \end{cases}$$



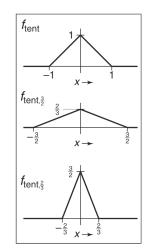
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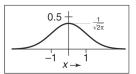
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Tent filter

$$f_{ ext{tent}}(x) = egin{cases} 1 - |x| & |x| < 1, \ 0 & ext{otherwise}; \ f_{ ext{tent},r}(x) = rac{f_{ ext{tent}}(x/r)}{r}. \end{cases}$$



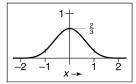
Gaussian filter



$$f_g(x) = \frac{1}{\sqrt{2\pi}}e^{-x^2/2}.$$

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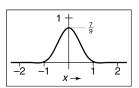
B-Spline cubic



$$f_B(x) = \frac{1}{6} \begin{cases} -3(1-|x|)^3 + 3(1-|x|)^2 + 3(1-|x|) + 1 & -1 \le x \le 1, \\ (2-|x|)^3 & 1 \le |x| \le 2, \\ 0 & \text{otherwise.} \end{cases}$$

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Michell-Netravali cubic

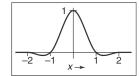


$$f_M(x) = \frac{1}{3} f_B(x) + \frac{2}{3} f_C(x)$$

$$= \frac{1}{18} \begin{cases} -21(1-|x|)^3 + 27(1-|x|)^2 + 9(1-|x|) + 1 & -1 \le x \le 1, \\ 7(2-|x|)^3 - 6(2-|x|)^2 & 1 \le |x| \le 2, \\ 0 & \text{otherwise.} \end{cases}$$

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Catmull-Rom cubic



$$f_C(x) = \frac{1}{2} \begin{cases} -3(1-|x|)^3 + 4(1-|x|)^2 + (1-|x|) & -1 \le x \le 1, \\ (2-|x|)^3 - (2-|x|)^2 & 1 \le |x| \le 2, \\ 0 & \text{otherwise.} \end{cases}$$

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Effects of reconstruction filters

- For some filters, the reconstruction process winds up implementing a simple algorithm
- Box filter (radius 0.5): nearest neighbor sampling

box always catches exactly one input point

it is the input point nearest the output point

so output[i, i] = input[round(x(i)), round(y(i))]

x(i) computes the position of the output coordinate i on the input grid

• Tent filter (radius 1): linear interpolation

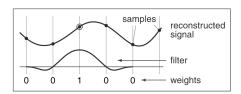
tent catches exactly 2 input points

weights are a and (1 - a)

result is straight-line interpolation from one point to the next

Properties of filters

- Degree of continuity
- Impulse response
- · Interpolating or no
- Ringing, or overshoot



interpolating filter used for reconstruction

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Ringing, overshoot, ripples

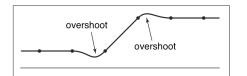
Overshoot

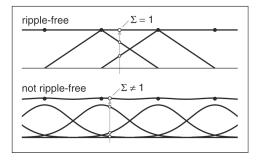
caused by negative filter values

Ripples

constant in, non-const. out ripple free when:

$$\sum_{i} f(x+i) = 1 \quad \text{for all } x.$$



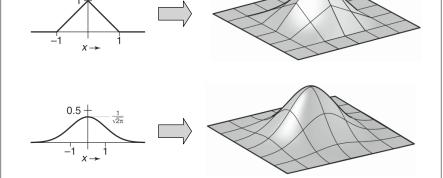


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Constructing 2D filters

• Separable filters (most common approach)



Yucky details

• What about near the edge?

the filter window falls off the edge of the image

need to extrapolate

methods:

- · clip filter (black)
- · wrap around
- · copy edge
- reflect across edge
- · vary filter near edge



p or cerispair

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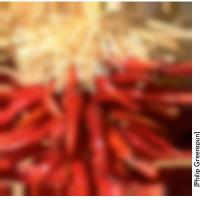
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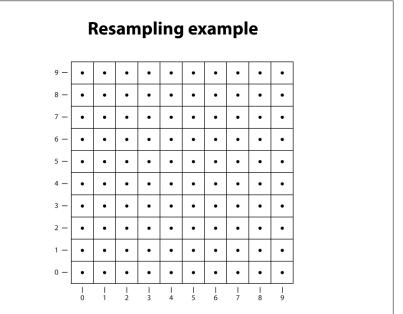


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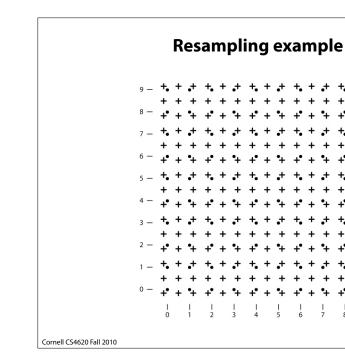
Reducing and enlarging

- · Very common operation devices have differing resolutions applications have different memory/quality tradeoffs
- Also very commonly done poorly
- Simple approach: drop/replicate pixels
- · Correct approach: use resampling

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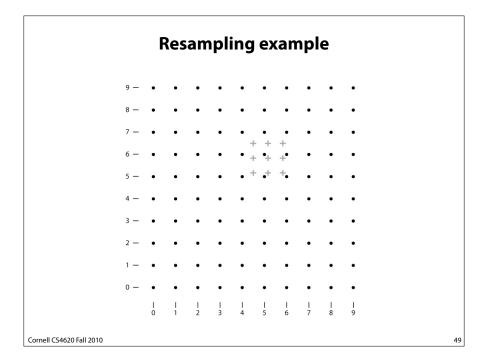


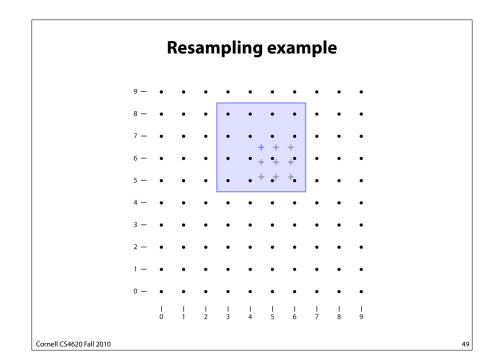
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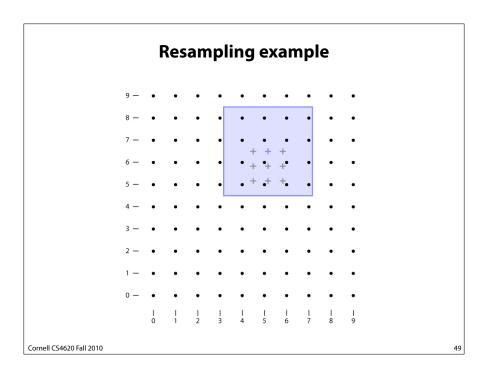


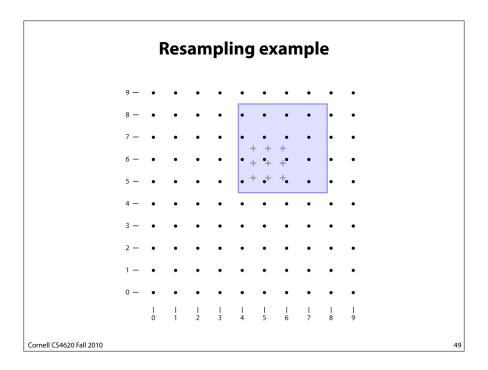
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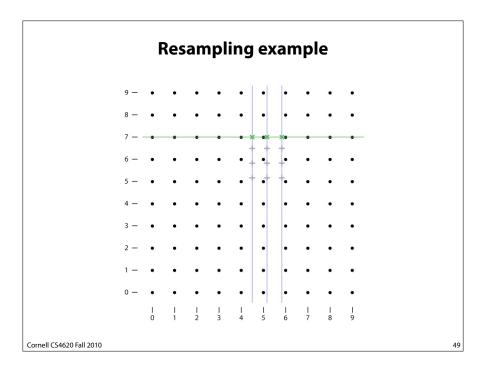
Resampling example 11 -Cornell CS4620 Fall 2010

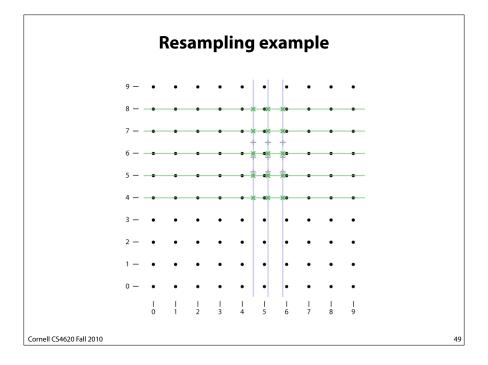


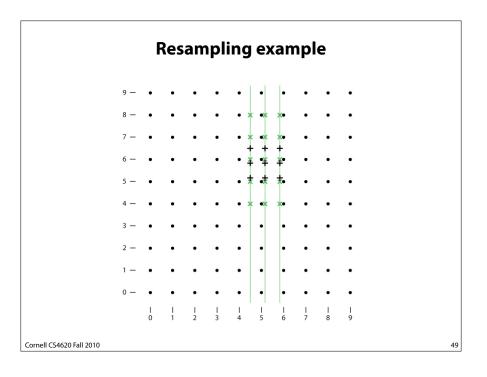






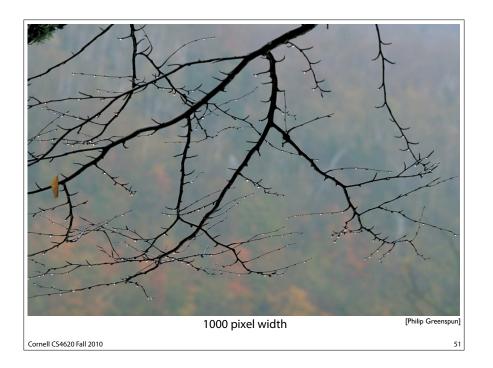


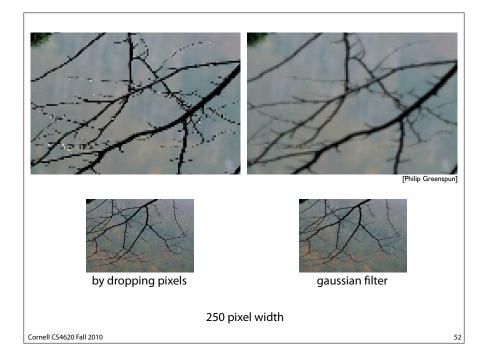




Reducing and enlarging

- Very common operation
 devices have differing resolutions
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Types of artifacts

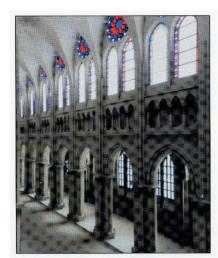
- Garden variety
 what we saw in this natural image
 fine features become jagged or sparkle
- Moiré patterns

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600ppi scan of a color halftone image

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by dropping pixels

gaussian filter

downsampling a high resolution scan

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Types of artifacts

- Garden variety
 what we saw in this natural image
 fine features become jagged or sparkle
- Moiré patterns

 caused by repetitive patterns in input
 produce large-scale artifacts; highly visible
- These artifacts are aliasing just like in the audio example earlier
- How do I know what filter is best at preventing aliasing?
 practical answer: experience
 theoretical answer: there is another layer of cool math behind all this
 - based on Fourier transforms
 - provides much insight into aliasing, filtering, sampling, and reconstruction

