Image Processing and Computer Vision Joachim Weickert, Summer Term 2019	N	A
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Image Interpolation	3	4
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Motivation (1)	M		1
Motivation	1	7	2
	3	4	4
What is Interpolation?	5		6
<ul> <li>recovery of continuous data from exact discrete data inside the data interval</li> </ul>	7	8	8
<ul> <li>inverse step to sampling, where discrete data are created from continuous ones</li> </ul>	9	1	.0
(see Lectures 1 and 5)	11	1	2
◆ always involves assumptions on the data, e.g. smoothness or band limitation	13	1	4
(although these assumptions are not always stated explicitly)	15	1	6
<ul> <li>must be distinguished from</li> </ul>	17	1	8
• extrapolation: uses a model outside the given data interval;	19	2	0
example: weather forecast	21	2	2
<ul> <li>approximation: model does not reproduce the given discrete data exactly; example: regression curve through noisy data</li> </ul>	23	2	24
A improved the sign that is make twented adaptive to be made to the bank to the	25	2	26
<ul> <li>important topic that is not treated adequately in most text books</li> </ul>	27	2	28
	29	3	0

#### Motivation (2)

#### Where is Interpolation Necessary?

- rescaling, zooming:
  - increase the apparent resolution of images
  - examples: "digital zooms" in cameras, video upscaling
- reslicing:
  - display a (medical) 3-D data set along arbitrary planes that do not coincide with the measured planes along the axis directions
- all kinds of geometric transformations, e.g.
  - image translation with subpixel precision
  - image rotation
  - warping in order to compensate for motion in image sequences
  - registration of medical images
  - ultrasound scan conversion from polar to cartesian coordinates
  - compensation of pincushion and barrel lens distortions (kissen- und tonnenförmige Verzeichnungen)

#### Motivation (3)



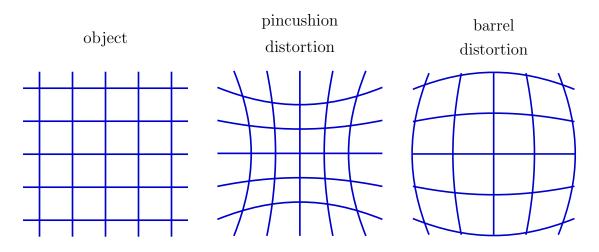




**Top:** Original image. **Bottom left:** Optical zoom with a factor 10. **Bottom right:** "Digital zoom". Source: http://www.cambridgeincolour.com/tutorials/image-interpolation.htm.

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# Motivation (4)



Most optical lens systems – in particular so-called "super zooms" – suffer from pincushion or barrel distortions. Compensating these distortions in digital images requires interpolation methods. Modern cameras can correct this automatically with their interpolation firmware. Author: M. Mainberger.

# Basic Structure of Classical Interpolation (1)

# **Basic Structure of Classical Interpolation**

# **Classical Interpolation**

- Consider an infinitely extended (e.g. by reflection) m-dimensional discrete signal  $(f_{k})$  on an equidistant grid with  $k = (k_{1}, k_{2}, ..., k_{m})^{\top} \in \mathbb{Z}^{m}$  (grid size 1). Example for m = 2: image  $(f_{i,j})$  with  $(i,j)^{\top} \in \mathbb{Z}^{2}$ .
- Compute a continuous signal u(x) as a weighted average of the discrete samples  $\{f_{\pmb{k}}\,|\, \pmb{k}\in\mathbb{Z}^m\}$ :

$$u(\boldsymbol{x}) = \sum_{\boldsymbol{k} \in \mathbb{Z}^m} f_{\boldsymbol{k}} \, \varphi_{\text{int}}(\boldsymbol{x} \! - \! \boldsymbol{k})$$

for all  $\mathbf{x} = (x_1, x_2, ..., x_m)^{\top} \in \mathbb{R}^m$ .

• The only remaining freedom lies in the *synthesis function*  $\varphi_{int} : \mathbb{R}^m \to \mathbb{R}$ . It determines the weights.

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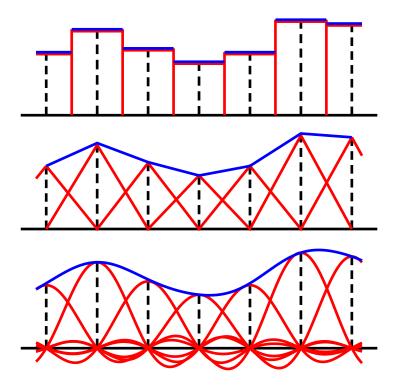
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#### **Basic Structure of Classical Interpolation (2)**



Different synthesis functions (red) and their interpolant (blue). The discrete data are drawn in black. **Top:** Nearest neighbour interpolation uses box functions as synthesis functions. **Middle:** Linear interpolation uses hat functions. **Bottom:** Interpolation with sinc functions. Author: M. Mainberger.

# **Basic Structure of Classical Interpolation (3)**

# A Popular Condition for Synthesis Functions

# Interpolation Condition

With our interpolation formula

$$u(\boldsymbol{x}) = \sum_{\boldsymbol{k} \in \mathbb{Z}^m} f_{\boldsymbol{k}} \, \varphi_{\text{int}}(\boldsymbol{x} - \boldsymbol{k})$$

the interpolation condition  $u({m n})=f_{m n}$  for all  ${m n}\in{\mathbb Z}^m$  is trivial to guarantee if

$$\varphi_{\mathrm{int}}(\boldsymbol{x}) = \left\{ \begin{array}{ll} 1 & \text{for } \boldsymbol{x} = (0,...,0)^\top, \\ 0 & \text{for } \boldsymbol{x} \in \mathbb{Z}^m \setminus \{(0,...,0)^\top\}. \end{array} \right.$$

This condition fixes  $\varphi_{\rm int}$  at integer arguments, but not inbetween. For non-integer arguments,  $\varphi_{\rm int}(x)$  can be tuned to specific applications.

- This condition is sufficient for interpolation, but not necessary.
- Synthesis functions satisfying this interpolation condition are called interpolating synthesis functions.

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# **Basic Structure of Classical Interpolation (4)**

#### **Desirable Properties of the Synthesis Function**

#### Separability

$$arphi_{\mathrm{int}}(oldsymbol{x}) = \prod_{i=1}^m ilde{arphi}_{\mathrm{int}}(x_i) \qquad \text{for all } oldsymbol{x} = (x_1, x_2, ..., x_m)^{ op} \in \mathbb{R}^m$$

- ullet allows simple and efficient  $m ext{-}D$  implementations using 1-D interpolations
- equal treatment of all axes

#### Symmetry

$$arphi_{\mathrm{int}}(oldsymbol{x}) = arphi_{\mathrm{int}}(-oldsymbol{x}) \qquad ext{for all } oldsymbol{x} \in \mathbb{R}^m$$

- equal treatment of opposite sides
- weaker requirement than rotation invariance

#### Partition of Unity

$$\sum_{{\boldsymbol k}\in\mathbb{Z}^m} \varphi_{\rm int}({\boldsymbol x}\!-\!{\boldsymbol k}) = 1 \qquad \text{for all } {\boldsymbol x}\in\mathbb{R}^m$$

• guarantees that a constant signal is reproduced exactly

# **Basic Structure of Classical Interpolation (5)**

# How Can One Judge the Quality of a Good Interpolant?

# ♦ Small Support Region of the Synthesis Function

- size of the region where  $\varphi_{int}$  does not vanish (support region) should be small
- allows fast computation involving only a few neighbours

# ♦ High Approximation Order

- Let us interpolate samples of a smooth function f. Let the grid size h go to 0. If the error between the interpolant u and f is  $\mathcal{O}(h^p)$ , then p is called approximation order.
- Larger p indicate better approximation qualities (faster error decay).
- ullet equivalent to the exact reproduction of all polynomials of degree  $\leq p-1$

# High Regularity

- The interpolant should be as smooth as possible, i.e. it should belong to the set  $C^k$  of k-times continuously differentiable functions with a large k.
- allows to compute higher order derivatives analytically, e.g. for feature detection

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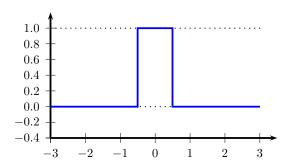
# Synthesis Functions for Classical Interpolation (1)

# Synthesis Functions for Classical Interpolation (in 1-D)

#### ◆ Nearest Neighbour Interpolation

$$\varphi_{\rm int}(x) = \begin{cases} 1 & \text{for } |x| < \frac{1}{2}, \\ \frac{1}{2} & \text{for } |x| = \frac{1}{2}, \\ 0 & \text{else.} \end{cases}$$

- very small support interval:  $\left[-\frac{1}{2},\frac{1}{2}\right]$
- lowest approximation order: p=1 (reproduces constant functions)
- leads to a discontinuous interpolant



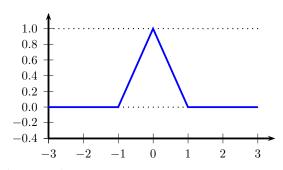
Synthesis function for nearest neighbour interpolation. Author: M. Mainberger.

# Synthesis Functions for Classical Interpolation (2)

# **♦** Linear Interpolation

$$\varphi_{\rm int}(x) = \left\{ \begin{array}{ll} 1 - |x| & {\rm for} \ |x| < 1, \\ 0 & {\rm else} \end{array} \right.$$

- ullet small support interval: [-1,1]
- approximation order p=2 (reproduces linear functions)
- ullet gives a continuous  $(C^0)$  interpolant



Synthesis function for linear interpolation. Author: M. Mainberger.

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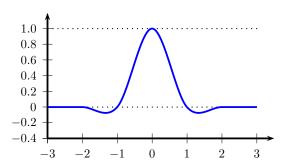
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# Synthesis Functions for Classical Interpolation (3)

• Keys Interpolation (with  $a = -\frac{1}{2}$ )

$$\varphi_{\mathrm{int}}(x) = \begin{cases} \frac{3}{2}|x|^3 - \frac{5}{2}x^2 + 1 & \text{for } |x| < 1, \\ -\frac{1}{2}|x|^3 + \frac{5}{2}x^2 - 4|x| + 2 & \text{for } 1 \leq |x| < 2, \\ 0 & \text{else.} \end{cases}$$

- support interval [-2, 2]
- approximation order p=3 (reproduces quadratic functions)
- ullet creates a continuously differentiable  $(C^1)$  interpolant



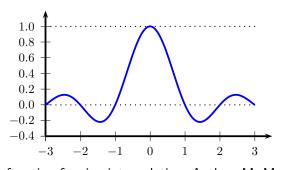
Synthesis function for Keys interpolation. Author: M. Mainberger.

# Synthesis Functions for Classical Interpolation (4)

**♦** Sinc Interpolation

$$\varphi_{\text{int}}(x) = \text{sinc}(\pi x) = \frac{\sin(\pi x)}{\pi x}$$

- infinite (!) support interval  $(-\infty, \infty)$
- gives the exact (!) reconstruction for a bandlimited signal that has been sampled according to the sampling theorem (cf. Lecture 5)
- ullet yields an infinitely times differentiable  $(C^\infty)$  interpolant
- difficult to implement exactly due to its infinite support and its slow decay: usually approximated by truncated or windowed sinc functions



Synthesis function for sinc interpolation. Author: M. Mainberger.

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# Synthesis Functions for Classical Interpolation (5)

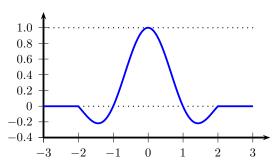
#### **♦** Truncated Sinc Interpolation

- truncates the sinc function outside some interval [-n, n],  $n \in \mathbb{N}$
- gives the so-called *Dirichlet apodisation*

$$\varphi_{\rm int}(x) = \left\{ \begin{array}{ll} \frac{\sin(\pi x)}{\pi x} & \text{for } |x| \leq n, \\ 0 & \text{else.} \end{array} \right.$$

- Unfortunately, this leads only to a  $C^0$  interpolant.
- This does not even satisfy the partition of unity!

  Thus, it may create severe shifts in the average grey level of the image.



Synthesis function for Dirichlet apodisation (n = 2). Author: M. Mainberger.

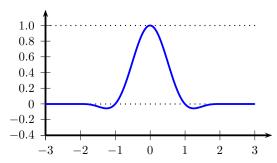
# Synthesis Functions for Classical Interpolation (6)

# **♦ Windowed Sinc Interpolation**

- ullet multiplies the sinc function with a smooth window of support [-n,n],  $n\in\mathbb{N}$
- using e.g. a so-called *Hanning window* gives the *Hanning apodisation*

$$\varphi_{\rm int}(x) = \left\{ \begin{array}{ll} \frac{\sin(\pi x)}{\pi x} \left(\frac{1}{2} + \frac{1}{2}\cos\left(\frac{\pi x}{n}\right)\right) & \text{for } |x| \leq n, \\ 0 & \text{else.} \end{array} \right.$$

- ullet creates a  $C^1$  interpolant
- violates partition of unity as well, leading to greyscale shifts



Synthesis function for Hanning apodisation (n=2). Author: M. Mainberger.

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# **Generalised Interpolation (1)**

# **Generalised Interpolation**

#### **Motivation**

• So far we have considered classical interpolation methods, where a weighted average of the *function values*  $\{f_{\mathbf{k}} | \mathbf{k} \in \mathbb{Z}^m\}$  is computed:

$$u(\boldsymbol{x}) = \sum_{\boldsymbol{k} \in \mathbb{Z}^m} f_{\boldsymbol{k}} \, \varphi_{\mathrm{int}}(\boldsymbol{x} - \boldsymbol{k}).$$

◆ In practice, this restricts the choice of suitable synthesis functions:

We used interpolating synthesis functions that satisfy the *interpolation condition* 

$$\varphi_{\mathrm{int}}(\boldsymbol{x}) = \left\{ \begin{array}{ll} 1 & \text{for } \boldsymbol{x} = (0,...,0)^\top, \\ 0 & \text{for } \boldsymbol{x} \in \mathbb{Z}^m \setminus \{(0,...,0)^\top\}. \end{array} \right.$$

- It is possible to obtain novel, better methods when we
  - permit coefficients that do not coincide with the function values
  - and do not insist on the interpolation condition ?

# Generalised Interpolation (2)

#### **Basic Idea Behind Generalised Interpolation**

◆ Consider the *generalised interpolation* formula

$$u(\boldsymbol{x}) = \sum_{\boldsymbol{k} \in \mathbb{Z}^m} c_{\boldsymbol{k}} \, \varphi(\boldsymbol{x} - \boldsymbol{k}).$$

- The unknown coefficients  $\{c_{\mathbf{k}} \mid \mathbf{k} \in \mathbb{Z}^m\}$  must be computed (details later): They depend on the function values  $\{f_{\mathbf{k}} \mid \mathbf{k} \in \mathbb{Z}^m\}$  and the synthesis function  $\varphi$ .
- The synthesis function  $\varphi$  can be *noninterpolating*: It does not have to fullfil the interpolation condition (we write  $\varphi$  instead of  $\varphi_{int}$ ).
- Generalised interpolation proceeds in two steps:
  - ullet compute the coefficients  $\{c_{oldsymbol{k}}\,|\, oldsymbol{k} \in \mathbb{Z}^m\}$
  - interpolate with the preceding formula
- ◆ This two-step procedure can pay off in terms of interpolation quality: Noninterpolating synthesis functions with a finite support can be equivalent to interpolating synthesis functions with an infinite support.

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# Generalised Interpolation (3)

# **Desirable Properties of Noninterpolating Synthesis Functions**

◆ Just as for interpolating synthesis functions, separability and symmetry are useful.

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◆ Partition of unity must be modified: One can show that

$$\sum_{{\boldsymbol k}\in{\mathbb Z}^m}\varphi({\boldsymbol x}\!-\!{\boldsymbol k}) \;=\; \frac{1}{c_{\boldsymbol 0}} \qquad \text{for all } {\boldsymbol x}\in{\mathbb R}^m$$

guarantees that a constant signal is reproduced exactly.

#### Quality Criteria of a Good Generalised Interpolant

- ◆ We have the same criteria as for a classical interpolant:
  - small support region of the synthesis function
  - high approximation order
  - high regularity
- Moreover, it should be easy to compute the coefficients  $\{c_{\mathbf{k}} \mid \mathbf{k} \in \mathbb{Z}^m\}$ .

# Generalised Interpolation (4)

# **How Are the Coefficients Computed?**

- For the sake of simplicity, consider the 1-D case with *finitely* many equidistant interpolation data  $f_1$ ,  $f_2$ ,...,  $f_N$  at the points  $x_1 = 1$ ,  $x_2 = 2$ , ...,  $x_N = N$ .
- lacktriangle For a given synthesis function arphi, the conditions  $u(i)=f_i$  for i=1,...,N yield

$$\sum_{k=1}^{N} c_k \, \varphi(i-k) = f_i \quad \text{for } i = 1, \dots, N.$$

lacktriangle This describes a linear system of N equations for the N unknowns  $c_1$ ,  $c_2$ , ...,  $c_N$ :

$$\begin{pmatrix} \varphi(0) & \varphi(1) & \dots & \varphi(N-1) \\ \varphi(1) & \varphi(0) & \dots & \varphi(N-2) \\ \vdots & \vdots & \dots & \vdots \\ \varphi(N-1) & \varphi(N-2) & \dots & \varphi(0) \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \\ \vdots \\ c_N \end{pmatrix} = \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ f_N \end{pmatrix}$$

where we have used the symmetry condition  $\varphi(x)=\varphi(-x).$ 

lacktriangle If arphi has a small support, then we have a band matrix with a small band.

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#### Which Synthesis Functions Are Used?

- The most popular synthesis functions are derived from so-called *B-splines*.
- We start with the box function for nearest neighbour interpolation. We define it as synthesis function  $\beta_0$ :

$$\beta_0(x) = \begin{cases} 1 & \text{for } |x| < \frac{1}{2}, \\ \frac{1}{2} & \text{for } |x| = \frac{1}{2}, \\ 0 & \text{else.} \end{cases}$$

The synthesis functions  $\beta_n$  with n=1,2,... are derived iteratively by convolution with  $\beta_0$  (see also Assignment H1, Problem 2):

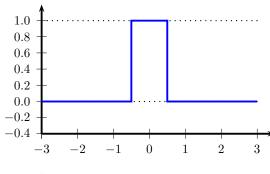
$$\beta_1 = \beta_0 * \beta_0,$$

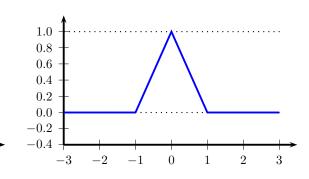
$$\beta_2 = \beta_1 * \beta_0 ,$$

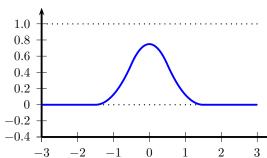
$$\beta_3 = \beta_2 * \beta_0.$$

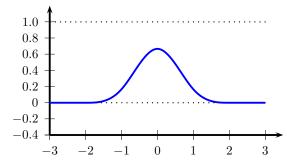
For  $n \ge 1$ , the synthesis function  $\beta_n$  is a piecewise polynomial of degree n. It is symmetric in 0, and n-1 times continuously differentiable.

# **Generalised Interpolation (6)**









The first four synthesis functions derived from B-splines. **Top left:**  $\beta_0$ . **Top right:**  $\beta_1$ . **Bottom left:**  $\beta_2$ . Bottom right:  $\beta_3$ . Note that  $\beta_0$  and  $\beta_1$  satisfy the interpolation condition, while  $\beta_2$  and  $\beta_3$  are noninterpolating synthesis functions with  $\beta_i(0) \neq 1$ . Author: M. Mainberger.

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# **Generalised Interpolation (7)**

#### **Explicit Formulas for the B-Spline Synthesis Functions**

$$\beta_0(x) = \begin{cases} 1 & \text{for } |x| < \frac{1}{2}, \\ \frac{1}{2} & \text{for } |x| = \frac{1}{2}, \\ 0 & \text{else,} \end{cases}$$

$$eta_1(x) = \left\{ egin{array}{ll} 1-|x| & {
m for} \ |x|<1, \ 0 & {
m else,} \end{array} 
ight.$$

$$\beta_2(x) = \begin{cases} \frac{3}{4} - x^2 & \text{for } |x| < \frac{1}{2}, \\ \frac{1}{2}(\frac{3}{2} - |x|)^2 & \text{for } \frac{1}{2} \le |x| < \frac{3}{2}, \\ 0 & \text{else,} \end{cases}$$

$$\beta_3(x) = \begin{cases} \frac{2}{3} - x^2 + \frac{1}{2}|x|^3 & \text{for } |x| < 1, \\ \frac{1}{6}(2 - |x|)^3 & \text{for } 1 \le |x| < 2, \\ 0 & \text{else.} \end{cases}$$

# **Generalised Interpolation (8)**

#### **Cubic B-Spline Interpolation**

- most popular generalised interpolation
- uses synthesis function  $\beta_3$
- support interval [-2, 2].
- can be shown to have approximation order p=4 (reproduces cubic functions)
- creates a twice continuously differentiable  $(C^2)$  interpolant
- one order better than Keys interpolation which has the same support interval
- offers good cost-performance ratio

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# Generalised Interpolation (9)

#### Finding the Coefficients for Cubic B-Spline Interpolation

• synthesis function  $\beta_3$  at integer values gives

$$\beta_3(k) \; = \; \left\{ \begin{array}{l} \frac{2}{3} \quad \text{for } k=0, \\ \frac{1}{6} \quad \text{for } k=\pm 1, \\ 0 \quad \text{for other integer values } k. \end{array} \right.$$

• leads to the following tridiagonal system for the interpolation coefficients:

$$\begin{pmatrix} \frac{2}{3} & \frac{1}{6} & 0 & \dots & 0 \\ \frac{1}{6} & \frac{2}{3} & \frac{1}{6} & 0 & \dots & 0 \\ & \ddots & \ddots & \ddots & \\ & & \ddots & \ddots & \ddots & \\ 0 & \dots & 0 & \frac{1}{6} & \frac{2}{3} & \frac{1}{6} \\ 0 & \dots & 0 & \frac{1}{6} & \frac{2}{3} \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \\ \vdots \\ \vdots \\ c_{N-1} \\ c_N \end{pmatrix} = \begin{pmatrix} f_1 \\ f_2 \\ \vdots \\ \vdots \\ f_{N-1} \\ f_N \end{pmatrix}.$$

• can be solved efficiently with the so-called Thomas algorithm (Lecture 17)

# Experiments (1)

# **Experiments**

- Consider a rotationally invariant test image.
- Perform 15 rotations by  $\frac{360}{15}$  degrees. The output of any step is used as input of the next step. Each rotation requires interpolation.
- For an ideal interpolant, the resulting image should be identical to the original one.

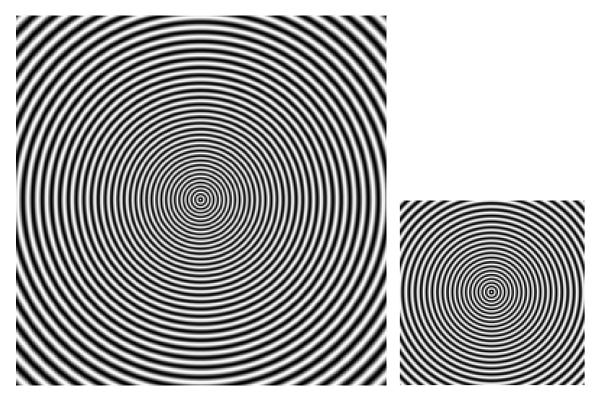
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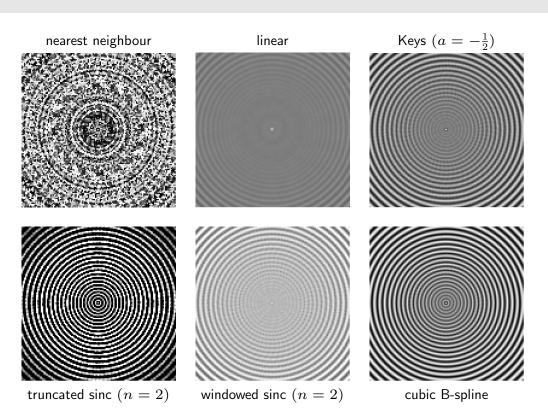
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# Experiments (2)



Left: Test image. Right: Central square. Authors: P. Thévenaz, T. Blu, M. Unser.

# Experiments (3)



Comparison of different interpolants after 15 rotations with  $\frac{360}{15}$  degrees. Note also the grey level shifts for truncated and windowed sinc interpolation. Authors: P. Thévenaz, T. Blu, M. Unser.

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Summary	M	I A
Summary	1	2
	3	4
◆ Interpolation recovers continuous data from discrete samples.	5	6
◆ Classical interpolation involves	7	8
• the function values,	9	10
• a synthesis function that satisfies the interpolation condition.	11	12
• Examples: nearest neighbour, linear, Keys, sinc interpolation	13	14
<ul> <li>Generalised interpolation renounces the interpolation condition.</li> </ul>	15	<b>16</b>
It requires to compute the weight coefficients.	17	18
This extra effort can be rewarded by better quality.	19	20
	21	22
<ul> <li>Example: Cubic spline interpolation.</li> <li>It offers a favourable cost-performance ratio.</li> </ul>	23	24
	25	26
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#### References

# References

When it comes to interpolation, you better forget about text books and consult the following articles instead:

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   (provides interesting historical facts)