

# **Multi-variate Polynomial Interpolation**

## Nested application of uni-variate methods

### 1. Bilinear interpolation on regular grids

Applications of interpolation methods often include multi-dimensional data and thus <u>several variables</u> asking for extension of the uni-variate interpolation methods. These extensions normally are a <u>nested</u> <u>application of uni-variate methods</u> and thus are rather natural.

**Example 1.1**: In <u>image processing</u> software tools <u>upsizing a raster image often is performed by a two-dimensional interpolation</u>. The figure below shows a small sample from the pixel raster, a so-called <u>patch</u>: The pixel coordinates (14,20), (14,21), (15, 20), (15,21) form the corners of a <u>square grid</u> with known real pixel values 91/255, 162/255, 210/255, 95/255. These correspond to color information, e.g. values of the red channel in a RGB-image (R = Red, G = Green, B = Blue).

Interpolating this 2-dimensional grid means finding a polynomial p(x, y) in two variables  $\{x, y\}$  such that *p* collocates with the color values in the four corner points of the grid.



Figure 1.1ab: Square grid (patch) and its bilinear interpolation (red channel values).

Of course, the question arises how to <u>represent</u> the multi-variate polynomial p(x, y) and how to determine the <u>order of this polynomial</u>. For the purpose of Example 1.1 we need four polynomial coefficients because there are four conditions. Preferring Newton polynomials leads to the following straightforward representation:

$$p(x, y) = a_{0,0}\pi_0(x)\pi_0(y) + a_{1,0}\pi_1(x)\pi_0(y) + a_{0,1}\pi_0(x)\pi_1(y) + a_{1,1}\pi_1(x)\pi_1(y)$$

$$p(x, y) = a_{0,0}\mathbf{1}\cdot\mathbf{1} + a_{1,0}(x-x_0)\mathbf{1} + a_{0,1}\mathbf{1}(y-y_0) + a_{1,1}(x-x_0)(y-y_0)$$
(1)

This kind of representation is called a <u>2-fold tensor product</u> of the uni-variate basis  $\{\pi_0, \pi_1\}$  in the variables  $\{x, y\}$ . It is also called <u>bilinear interpolation</u> because only uni-variate basis functions up to order 1 are used.



The figure below illustrates how 2-dimensional interpolation problems are solved by two consecutive uni-variate interpolation procedures. The *xy*-coordinate values have been rescaled to the unit square  $[0,1] \times [0,1]$ .



**Figure 1.2**: Illustration of 2-dimensional interpolation on a unit square. The red-gray surface is given by the polynomial  $0.356863 + 0.466667 \times + 0.278431 \text{ y} - 0.729412 \times \text{ y}$  in scaled *xy*-coordinates and otherwise by -215.98 + 15.0549 x + 10.4902 y - 0.729412 x y.

The computation proceeds along the following steps. Each step applies the method of divided differences.

(1) Uni-variate interpolation in the variable x for  $y = y_0 = 20$  leading to

$$p(x, y_0) = p(x_0, y_0)\pi_0(x) + \frac{p(x_1, y_0) - p(x_0, y_0)}{x_1 - x_0}\pi_1(x) =$$

$$91/255 \cdot 1 + \frac{210/255 - 91/255}{15 - 14} \cdot (x - 14)$$

(2) Uni-variate interpolation in the variable x for  $y = y_1 = 21$  leading to



$$p(x, y_1) = p(x_0, y_1)\pi_0(x) + \frac{p(x_1, y_1) - p(x_0, y_1)}{x_1 - x_0}\pi_1(x) = \frac{162/255 \cdot 1 + \frac{95/255 - 162/255}{15 - 14} \cdot (x - 14)}{15 - 14}$$

(3) Uni-variate interpolation in the variable y for an arbitrary value of x. This corresponds to interpolating the two high-lighted points in Fig. 1.2. From the steps (1) and (2) we compute the values  $p(x, y_0)$  and  $p(x, y_1)$  and then interpolate these values along the *y*-axis:

$$p(x,y) = p(x,y_0)\pi_0(y) + \frac{p(x,y_1) - p(x,y_0)}{y_1 - y_0}\pi_1(y) = \left(\frac{91/255 \cdot 1 + \frac{210/255 - 91/255}{15 - 14} \cdot (x - 14)}{15 - 14} \cdot (x - 14)\right) \cdot 1 + \frac{162/255 \cdot 1 + \frac{95/255 - 162/255}{15 - 14} \cdot (x - 14) - 91/255 \cdot 1 + \frac{210/255 - 91/255}{15 - 14} \cdot (x - 14)}{21 - 20} \cdot (y - 20)$$

The latter expression simplifies to -215.98 + 15.0549 x + 10.4902 y - 0.729412 x y.

From these computations it is seen that <u>multi-variate interpolation is a nested application of uni-variate</u> interpolation along different coordinate axes.

#### 2. Bi-cubic interpolation on regular grids

Bi-cubic interpolation is a straightforward generalization of the method developped in the previous section. The term bi-cubic means that the basis polynomials are constituted by a 2-fold tensor product of the univariate cubic basis  $\{\pi_0, \pi_1, \pi_2, \pi_3\}$  in the variables  $\{x, y\}$ .

$$p(x, y) = a_{0,0}\pi_{0}(x)\pi_{0}(y) + a_{1,0}\pi_{1}(x)\pi_{0}(y) + a_{2,0}\pi_{2}(x)\pi_{0}(y) + a_{3,0}\pi_{3}(x)\pi_{0}(y) + a_{0,1}\pi_{0}(x)\pi_{1}(y) + a_{1,1}\pi_{1}(x)\pi_{1}(y) + a_{2,1}\pi_{2}(x)\pi_{1}(y) + a_{3,1}\pi_{3}(x)\pi_{1}(y) + a_{0,2}\pi_{0}(x)\pi_{2}(y) + a_{1,2}\pi_{1}(x)\pi_{2}(y) + a_{2,2}\pi_{2}(x)\pi_{2}(y) + a_{3,2}\pi_{3}(x)\pi_{2}(y) + a_{0,3}\pi_{0}(x)\pi_{3}(y) + a_{1,3}\pi_{1}(x)\pi_{3}(y) + a_{2,3}\pi_{2}(x)\pi_{3}(y) + a_{3,3}\pi_{3}(x)\pi_{3}(y)$$

$$(2)$$

From this it is seen that 16 conditions are required because there are 16 unknown coefficients.

#### 2.1 Bi-cubic collocation

Bi-cubic collocation provides 16 function values on a <u>regular 4x4 grid</u>. These values constitute a set of 16 conditions (as required).



Figure 1.3: Illustration of 2-dimensional bi-cubic interpolation on a 4x4 grid.

The computation proceeds along the following uni-variate interpolation steps:

**Steps (1)-(4)**: Uni-variate interpolations in the variable *x* for  $y = y_0, y_1, y_2, y_3$  leading to 4 cubic polynomials  $p(x, y_0), p(x, y_1), p(x, y_2), p(x, y_3)$ .

**Step (5)**: Uni-variate interpolation in the variable *y* for an arbitrary value of *x*. This corresponds to interpolating the four high-lighted points in Fig. 1.3. From the steps (1) to (4) we compute the values  $p(x, y_0)$ ,  $p(x, y_1)$ ,  $p(x, y_2)$  and  $p(x, y_3)$  and then interpolate these values along the *y*-axis.

This finally leads to the numerical bi-cubic polynomial

-0.581324 + 3.58038 x - 2.92226 x<sup>2</sup> + 0.63402 x<sup>3</sup> + 1.15278 y + 6.07605 x y - 6.55837 x<sup>2</sup> y + 1.35823 x<sup>3</sup> y - 0.181566 y<sup>2</sup> - 9.41581 x y<sup>2</sup> + 8.59978 x<sup>2</sup> y<sup>2</sup> - 1.72666 x<sup>3</sup> y<sup>2</sup> - 0.0584666 y<sup>3</sup> + 2.35529 x y<sup>3</sup> - 2.04092 x<sup>2</sup> y<sup>3</sup> + 0.402331 x<sup>3</sup> y<sup>3</sup>

in expanded form. The details of the computations are omitted.



### \*2.2 Bi-cubic osculation

When working with unit-square grids (as in the section on bi-linear interpolation and typical for image processing) 12 conditions on the derivative values must be added to the 4 values in the 4 corners  $\{(x_0, y_0), (x_0, y_1), (x_1, y_0), (x_1, y_1)\}$ .

Values for the first-order partial derivatives ...

$$\frac{\partial}{\partial x} p(x_0, y_0), \frac{\partial}{\partial x} p(x_0, y_1), \frac{\partial}{\partial x} p(x_1, y_0), \frac{\partial}{\partial x} p(x_1, y_1)$$
$$\frac{\partial}{\partial y} p(x_0, y_0), \frac{\partial}{\partial y} p(x_0, y_1), \frac{\partial}{\partial y} p(x_1, y_0), \frac{\partial}{\partial y} p(x_1, y_1)$$

... and the second-order partial derivatives

$$\frac{\partial^2}{\partial x \partial y} p(x_0, y_0), \frac{\partial^2}{\partial x \partial y} p(x_0, y_1), \frac{\partial^2}{\partial x \partial y} p(x_1, y_0), \frac{\partial^2}{\partial x \partial y} p(x_1, y_1)$$

constitute such a set of 12 conditions. Generally, the partial derivatives are approximated by finite differences of data values neighbouring the corners.

The 4 cubic boundary curves (of the polynomial surface)

 $p(x, y_0), p(x, y_1), p(x_0, y)$  and  $p(x_1, y)$ 

can be computed by <u>Hermite interpolation</u> using divided differences and the informations on the first-order partial derivatives.

### 3. Multi-variate collocation on regular grids<sup>1</sup>

Multi-variate collocation problems on regular grids are solved along the same lines as the 2dimensional collocation problems described in the sections above.

The *x*-arguments now are vectors  $\vec{x}_0, \vec{x}_1, \dots, \vec{x}_{n-1}, \vec{x}_n$  of dimension *d* and thus we need basis functions which take vectors as inputs (i.e. functions in several variables). For practical purposes most widely used are <u>tensor products</u> of uni-variate basis functions.

If  $g_0, g_1, ..., g_m = \{g_j\}_{j=0,...,m}$  is a uni-variate basis then the <u>*d*-fold tensor product</u>

$$\sum_{j_1=0}^{m_1} \sum_{j_2=0}^{m_2} \cdots \sum_{j_d=0}^{m_d} a_{j_1, j_2, \dots, j_d} g_{j_1}(x^{(1)}) g_{j_2}(x^{(2)}) \cdots g_{j_d}(x^{(d)})$$
(3)

defines a basis of  $m_1 \times m_2 \times \cdots \times m_d$  functions in d variables  $x^{(1)}, x^{(2)}, \dots, x^{(d-1)}, x^{(d)}$ .

<sup>&</sup>lt;sup>1</sup> Interpolation on irregular (non-grid) data is solved by triangulation and working with triangle patches (elements). For the solution of the interpolation problem on a triangle patch barycentric coordinates are very useful.



Name of basis functions	3d-formulas
Polynomials	$ \begin{cases} x^{(1)j} x^{(2)k} x^{(3)l}   j,k,l \in N_0 \end{cases} \text{ (standard monomials)} \\ \\ \{ \pi_j(x^{(1)}) \pi_k(x^{(2)} \pi_l(x^{(3)})   j,k,l \in N_0 \} \text{ (Newton polynomials)} \end{cases} $
	$\left\{\!T_{j}(x^{(1)})T_{k}(x^{(2)}T_{l}(x^{(3)})\big j,k,l\in N_{0}\right\}$ (Chebyshev polynomials, $x^{(1)},x^{(2)},x^{(3)}\in(-1,\!1)$ )

**Table 1.1**: A few basis functions in 3 variables. The generalizations to more than 3 variables are straightforward.

Typical applications are tri-linear and tri-cubic interpolation. The latter often is used on unit cubic grids with informations on partial derivatives.