

Bivariate Blending Thiele-Werner's Osculatory Rational Interpolation

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Abstract

Both the expansive Newton's interpolating polynomial and the Thiele-Werner's interpolation are used to construct a kind of bivariate blending Thiele-Werner's osculatory rational interpolation. A recursive algorithm and its characteristic properties are given. An error estimation is obtained and a numerical example is illustrated.

Keywords: Bivariate blending interpolation; osculatory rational interpolation; Thiele-Werner's interpolation; error estimation.

Mathematics subject classification: 41A20, 65D05

1. Introduction

Given a set of real points $X_n = \{x_0, x_1, \dots, x_n\} \subset [a, b] \subset R$, a function $f(x)$ defined on set $[a, b]$ can be approximated by the expansive Newton's interpolating polynomials [5]

$$N_n(x) = \sum_{i=0}^n f[x_0, x_0, \dots, x_{i-1}, x_{i-1}, \overbrace{x_i, \dots, x_i}^l] \prod_{v=0}^{i-1} (x - x_v)^2 (x - x_i)^{l-1}.$$

An efficient and reliable method of rational interpolation was proposed by Werner [1979] who considers generalized Thiele interpolants of the form [1]

$$R^{(0)}(x) = p_0(x) + \frac{\omega_0(x)}{p_1(x)} + \frac{\omega_1(x)}{p_2(x)} + \dots + \frac{\omega_{t-1}(x)}{p_t(x)}.$$

In this formula, the polynomial

$$\omega_s(x) = \prod_{i=h_s}^{k_s} (x - x_i) \quad (s = 0, 1, \dots, t-1)$$

vanishes at the (possibly reordered) interpolation points $x_{h_s}, x_{h_s+1}, \dots, x_{k_s}$; $p_s(x)$ is a Newton interpolating polynomial which interpolates $f^{(s)}(x)$ on $x_{h_s}, x_{h_s+1}, \dots, x_{k_s}$. The data for each stage of the iterative construction of the fraction are defined by

$$f^{(s+1)}(x_i) = \frac{\omega_s(x_i)}{f^{(s)}(x_i) - p_s(x_i)},$$

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for $s = 0, 1, \dots, t - 1, i = h_{s+1}, h_{s+1} + 1, \dots, n, n = \sum_{s=0}^{t-1} (k_s - h_s + 1)$.

For simplicity and also without loss of generality, we restrict ourselves to the case where bivariate problems are involved [4] .

2. The construction of bivariate blending Thiele-Werner’s osculatory rational interpolation

We set $X_n = \{x_0, x_1, \dots, x_n\} \subset [a, b] \subset R, Y_m = \{y_0, y_1, \dots, y_m\} \subset [c, d] \subset R, \Pi_{x,y}^{n,m} = X_n \times Y_m$, and let a bivariate function $f(x, y)$ be defined on $D = [a, b] \times [c, d]$.

Now, we will construct a bivariate function $R(x, y)$ of the following form

$$R(x, y) = p_0(x, y) + \frac{(x - x_0)^2}{p_1(x, y)} + \frac{(x - x_1)^2}{p_2(x, y)} + \dots + \frac{(x - x_{n-1})^2}{p_n(x, y)}, \tag{2.1}$$

such that

$$R(x_i, y_j) = f(x_i, y_j), \quad \frac{\partial}{\partial x} R(x_i, y_j) = f_x(x_i, y_j), \quad \frac{\partial}{\partial y} R(x_i, y_j) = f_y(x_i, y_j). \tag{2.2}$$

Suppose $\varphi_i(x, y)$ ($i = 0, 1, \dots, n$) are bivariate functions defined on $D = [a, b] \times [c, d]$. We give the following two definitions firstly.

Definition 2.1. [5] For fixed x , let

$$\begin{aligned} \varphi_i[x; y] &= \varphi_i(x, y), \quad \varphi_i[x; y_j, y_j] = \frac{\partial}{\partial y} \varphi_i(x, y_j), \\ \varphi_i[x; y_p, y_q] &= \frac{\varphi_i[x; y_p] - \varphi_i[x; y_q]}{y_p - y_q}, \quad (p \neq q), \\ \varphi_i[x; y_0, y_0, \dots, y_p, \dots, y_p, y_k, \dots, y_k] & \\ &= \frac{\varphi_i[x; y_0, y_0, \dots, y_p, \dots, y_p, y_k, \dots, y_k] - \varphi_i[x; y_0, y_0, \dots, y_p, \dots, y_p, y_k, \dots, y_k]}{y_p - y_k}, \end{aligned}$$

where $h = 1, 2; l = 1, 2; 0 \leq p < k$ and p, k are non-negative integers. Then $\varphi_i[x; y_0, y_0, \dots, y_p, \dots, y_p, y_k, \dots, y_k]$ is called the expansive divided difference of Newton-type of $\varphi_i(x, y)$ at point sets with $\{x_0, \dots, x_n\} \times \{y_0, \dots, y_m\}$.

Definition 2.2. [5] For fixed x , let

$$\begin{aligned} \varphi_i[x, x; y] &= \frac{\partial \varphi_i(x, y)}{\partial x}, \\ \varphi_i[x, x; y_p, y_q] &= \frac{\varphi_i[x, x; y_q] - \varphi_i[x, x; y_p]}{y_q - y_p}, \\ \varphi_i[x, x; y_0, \dots, y_p, y_k] &= \frac{\varphi_i[x, x; y_0, \dots, y_{p-1}, y_k] - \varphi_i[x, x; y_0, \dots, y_p]}{y_k - y_p}, \end{aligned}$$

where $0 \leq p < k$, and p, k are non-negative integers. Then $\varphi_i[x, x; y_0, \dots, y_p, y_k]$ is called the divided difference of Newton-type of $\frac{\partial \varphi_i(x, y)}{\partial x}$ at the point sets with $\{x_0, \dots, x_n\} \times \{y_0, \dots, y_m\}$.

Secondly, we give our recursive algorithm. Let $\omega_j(y) = (y - y_0)(y - y_1) \cdots (y - y_j)$ for $j \geq 0$ and $\omega_{-1}(y) = 1$.

Algorithm 2.1

Step 1 Let $\varphi_0(x, y) = f(x, y), x \in [a, b]$,

$$p_0(x, y) = \sum_{j=0}^m \left(\varphi_0[x_0; y_0, y_0, y_1, \dots, y_{j-1}, y_j] \omega_{j-1}^2(y) + \varphi_0[x_0; y_0, y_0, y_1, \dots, y_j, y_j] \omega_{j-1}(y) \omega_j(y) \right) + (x - x_0) \left(\sum_{j=0}^m \varphi_0[x_0, x_0; y_0, y_1, \dots, y_{j-1}, y_j] \omega_{j-1}(y) \right).$$

Step 2 Let $\varphi_1(x, y) = \frac{(x-x_0)^2}{\varphi_0(x,y)-p_0(x,y)}, x \in [x_1, b]$,

$$p_1(x, y) = \sum_{j=0}^m \left(\varphi_1[x_1; y_0, y_0, y_1, \dots, y_{j-1}, y_j] \omega_{j-1}^2(y) + \varphi_1[x_1; y_0, y_0, y_1, \dots, y_j, y_j] \omega_{j-1}(y) \omega_j(y) \right) + (x - x_1) \left(\sum_{j=0}^m \varphi_1[x_1, x_1; y_0, y_1, \dots, y_{j-1}, y_j] \omega_{j-1}(y) \right).$$

⋮

Step (s+1) Let

$$\varphi_s(x, y) = \frac{(x - x_{s-1})^2}{\varphi_{s-1}(x, y) - p_{s-1}(x, y)} = \frac{(x - x_{s-1})^2}{-p_{s-1}(x, y) + \frac{(x - x_{s-2})^2}{-p_{s-2}(x, y) + \dots + \frac{(x - x_1)^2}{-p_1(x, y) + \varphi_0(x, y) - p_0(x, y)}}}, \quad x \in [x_s, b], \tag{2.3}$$

$$p_s(x, y) = \sum_{j=0}^m \left(\varphi_s[x_s; y_0, y_0, y_1, \dots, y_{j-1}, y_j] \omega_{j-1}^2(y) + \varphi_s[x_s; y_0, y_0, y_1, \dots, y_j, y_j] \omega_{j-1}(y) \omega_j(y) \right) + (x - x_s) \left(\sum_{j=0}^m \varphi_s[x_s, x_s; y_0, y_1, \dots, y_{j-1}, y_j] \omega_{j-1}(y) \right), \tag{2.4}$$

for $s = 2, 3, \dots, n - 1$.

So we have completed the construction of bivariate function $R(x, y)$ which is defined in (2.1) and $p_0(x, y), p_1(x, y), \dots, p_n(x, y)$ are defined by Algorithm 2.1. Next, we will prove two lemmas in order to show that the constructed function $R(x, y)$ satisfies the interpolation conditions in (2.2).

Lemma 2.1. Let $p_i(x, y)$ and $\varphi_i(x, y)$ be defined by Algorithm 2.1. Then $p_i(x, y)$ and $\varphi_i(x, y)$ satisfy:

$$p_i(x_i, y_j) = \varphi_i(x_i, y_j), \quad \frac{\partial}{\partial x} p_i(x_i, y_j) = \frac{\partial}{\partial x} \varphi_i(x_i, y_j), \quad \frac{\partial}{\partial y} p_i(x_i, y_j) = \frac{\partial}{\partial y} \varphi_i(x_i, y_j),$$

$$i = 0, 1, \dots, n, \quad j = 0, 1, \dots, m.$$

Proof. From (2.4), Definitions 2.1 and 2.2, we derive

$$p_i(x_i, y_j) = \varphi_i[x_i; y_0] + \varphi_i[x_i; y_0, y_0] \omega_0(y_j) + \dots + \varphi_i[x_i; y_0, y_0, \dots, y_{j-1}, y_{j-1}] \omega_{j-2}(y_j) \omega_{j-1}(y_j) + \varphi_i[x_i; y_0, y_0, \dots, y_{j-1}, y_j] \omega_{j-1}^2(y_j)$$

$$= \varphi_i[x_i; y_j] = \varphi_i(x_i, y_j), \tag{2.5}$$

$$\frac{\partial}{\partial x} p_i(x_i, y_j) = \varphi_i[x_i, x_i; y_0] + \varphi_i[x_i, x_i; y_0, y_1] \omega_0(y_j) + \dots$$

$$+ \varphi_i[x_i, x_i; y_0, y_1, \dots, y_{j-1}, y_j] \omega_{j-1}(y_j)$$

$$= \varphi_i[x_i, x_i; y_j] = \frac{\partial}{\partial x} \varphi_i(x_i, y_j), \tag{2.6}$$

$$\frac{\partial}{\partial y} p_i(x_i, y_j) = \frac{d}{dy} \left(\sum_{t=0}^m (\varphi_i[x_i; y_0, y_0, y_1, \dots, y_{t-1}, y_t] \omega_{t-1}^2(y) + \varphi_i[x_i; y_0, y_0, \dots, y_t, y_t] \omega_{t-1}(y) \omega_t(y)) \right) \Big|_{y=y_j}$$

$$= \varphi_i[x_i; y_j, y_j] = \frac{\partial}{\partial y} \varphi_i(x_i, y_j). \tag{2.7}$$

(2.5) and (2.7) can be proved by the properties of expansive Newton interpolating polynomials and (2.6) can be proved easily through the properties of Newton interpolating polynomials. ■

Lemma 2.2. For $0 \leq s \leq n$, let

$$R_s(x, y) = p_s(x, y) + \frac{(x - x_s)^2}{p_{s+1}(x, y) + p_{s+2}(x, y) + \dots + p_n(x, y)} \frac{(x - x_{s+1})^2}{p_n(x, y)}. \tag{2.8}$$

In particular, $R_0(x, y) = R(x, y)$, $R_n(x, y) = p_n(x, y)$. Then

(1) $R_s(x_t, y_j) = \varphi_s(x_t, y_j)$ holds true for $s = 0, 1, \dots, n$, $t = s, s + 1, \dots, n$, $j = 0, 1, \dots, m$.

(2)

$$\frac{\partial}{\partial x} R(x, y) = \frac{\partial}{\partial x} p_0(x, y) + \frac{2(x - x_0)}{R_1(x, y)} - \frac{(x - x_0)^2}{R_1^2(x, y)} \left\{ \frac{\partial}{\partial x} p_1(x, y) + \frac{2(x - x_1)}{R_2(x, y)} - \frac{(x - x_1)^2}{R_2^2(x, y)} \left(\dots - (x - x_{n-2})^2 \left(\frac{\partial}{\partial x} p_{n-1}(x, y) + \frac{2(x - x_{n-1}) p_n(x, y) - (x - x_{n-1})^2 \frac{\partial}{\partial x} p_n(x, y)}{p_n^2(x, y)} \right) \right) \right\}.$$

For simplicity, we denote it as:

$$\begin{aligned} \frac{\partial}{\partial x}R(x, y) &= \frac{\partial}{\partial x}p_0(x, y) + \frac{2(x - x_0)R_1(x, y) - (x - x_0)^2 \frac{\partial}{\partial x}p_1(x, y)}{R_1^2(x, y)} \\ &\quad - (x - x_0)^2 \frac{2(x - x_1)R_2(x, y) - (x - x_1)^2 \frac{\partial}{\partial x}p_2(x, y)}{R_2^2(x, y)} \\ &\quad - (x - x_1)^2 \frac{2(x - x_2)R_3(x, y) - (x - x_2)^2 \frac{\partial}{\partial x}p_3(x, y)}{R_3^2(x, y)} \\ &\quad - \dots \\ &\quad - (x - x_{n-2})^2 \frac{2(x - x_{n-1})p_n(x, y) - (x - x_{n-1})^2 \frac{\partial}{\partial x}p_n(x, y)}{p_n^2(x, y)}. \end{aligned}$$

(3)

$$\begin{aligned} \frac{\partial}{\partial y}R(x, y) &= \frac{\partial}{\partial y}p_0(x, y) - \frac{(x - x_0)^2}{R_1^2(x, y)} \times \left\{ \frac{\partial}{\partial y}p_1(x, y) - \frac{(x - x_1)^2}{R_2^2(x, y)} \right. \\ &\quad \times \left(\dots - \frac{(x - x_{n-2})^2}{R_{n-1}^2(x, y)} \left(\frac{\partial}{\partial y}p_{n-1}(x, y) + \frac{-(x - x_{n-1})^2 \frac{\partial}{\partial y}p_n(x, y)}{p_n^2(x, y)} \right) \right) \left. \right\}. \end{aligned}$$

For simplicity, we denote it as:

$$\begin{aligned} \frac{\partial}{\partial y}R(x, y) &= \frac{\partial}{\partial y}p_0(x, y) + \frac{-(x - x_0)^2 \frac{\partial}{\partial y}p_1(x, y)}{R_1^2(x, y)} \\ &\quad + [-(x - x_0)^2] \frac{-(x - x_1)^2 \frac{\partial}{\partial y}p_2(x, y)}{R_2^2(x, y)} \\ &\quad + [-(x - x_1)^2] \frac{-(x - x_2)^2 \frac{\partial}{\partial y}p_3(x, y)}{R_3^2(x, y)} \\ &\quad + \dots \\ &\quad + [-(x - x_{n-3})^2] \frac{-(x - x_{n-2})^2 \frac{\partial}{\partial y}p_{n-1}(x, y)}{R_{n-1}^2(x, y)} \\ &\quad + [-(x - x_{n-2})^2] \frac{-(x - x_{n-1})^2 \frac{\partial}{\partial y}p_n(x, y)}{p_n^2(x, y)}. \end{aligned}$$

Proof. (1) From (2.3) in Algorithm 2.1, Lemma 2.1 and (2.8), we get

$$\begin{aligned}
 R_s(x_t, y_j) &= p_s(x_t, y_j) + \frac{(x_t - x_s)^2}{p_{s+1}(x_t, y_j)} + \cdots + \frac{(x_t - x_{t-2})^2}{p_{t-1}(x_t, y_j)} + \frac{(x_t - x_{t-1})^2}{p_t(x_t, y_j)} \\
 &= p_s(x_t, y_j) + \frac{(x_t - x_s)^2}{p_{s+1}(x_t, y_j)} + \cdots + \frac{(x_t - x_{t-2})^2}{p_{t-1}(x_t, y_j)} + \frac{(x_t - x_{t-1})^2}{\varphi_t(x_t, y_j)} \\
 &= p_s(x_t, y_j) + \frac{(x_t - x_s)^2}{p_{s+1}(x_t, y_j)} + \cdots + \frac{(x_t - x_{t-2})^2}{p_{t-1}(x_t, y_j)} + \frac{(x_t - x_{t-1})^2}{\frac{(x_t - x_{t-1})^2}{\varphi_{t-1}(x_t, y_j) - p_{t-1}(x_t, y_j)}} \\
 &= p_s(x_t, y_j) + \frac{(x_t - x_s)^2}{p_{s+1}(x_t, y_j)} + \cdots + \frac{(x_t - x_{t-2})^2}{\varphi_{t-1}(x_t, y_j)} = \cdots \\
 &= p_s(x_t, y_j) + \frac{(x_t - x_s)^2}{\varphi_{s+1}(x_t, y_j)} = p_s(x_t, y_j) + \frac{(x_t - x_s)^2}{\frac{(x_t - x_s)^2}{\varphi_s(x_t, y_j) - p_s(x_t, y_j)}} \\
 &= \varphi_s(x_t, y_j).
 \end{aligned}$$

Moreover, (2) and (3) can be proved by induction. ■

Theorem 2.1. *Let*

$$R(x, y) = p_0(x, y) + \frac{(x - x_0)^2}{p_1(x, y)} + \frac{(x - x_1)^2}{p_2(x, y)} + \cdots + \frac{(x - x_{n-1})^2}{p_n(x, y)}, \tag{2.9}$$

where $p_i(x, y)$, ($i = 0, 1, \dots, n$) defined in Algorithm 2.1. Then

$$\begin{aligned}
 R(x_i, y_j) &= f(x_i, y_j), \quad \frac{\partial}{\partial x} R(x_i, y_j) = f_x(x_i, y_j), \\
 \frac{\partial}{\partial y} R(x_i, y_j) &= f_y(x_i, y_j), \quad \forall (x_i, y_j) \in \Pi_{x,y}^{n,m}.
 \end{aligned}$$

Proof.

(a) From (1) of Lemma 2.2, we know

$$R(x_i, y_j) = R_0(x_i, y_j) = \varphi_0(x_i, y_j) = f(x_i, y_j), \quad \forall (x_i, y_j) \in \Pi_{x,y}^{n,m}.$$

(b) From (2) of Lemma 2.2, we get

$$\begin{aligned}
 \frac{\partial}{\partial x} R(x_i, y_j) &= \frac{\partial}{\partial x} p_0(x_i, y_j) + \frac{2(x_i - x_0)R_1(x_i, y_j) - (x_i - x_0)^2 \frac{\partial}{\partial x} p_1(x_i, y_j)}{R_1^2(x_i, y_j)} \\
 &\quad - (x_i - x_0)^2 \frac{2(x_i - x_1)R_2(x_i, y_j) - (x_i - x_1)^2 \frac{\partial}{\partial x} p_2(x_i, y_j) - \cdots}{R_2^2(x_i, y_j)} \\
 &\quad - (x_i - x_{i-3})^2 \frac{2(x_i - x_{i-2})R_{i-1}(x_i, y_j) - (x_i - x_{i-2})^2 \frac{\partial}{\partial x} p_{i-1}(x_i, y_j)}{R_{i-1}^2(x_i, y_j)} \\
 &\quad - (x_i - x_{i-2})^2 \frac{2(x_i - x_{i-1})p_i(x_i, y_j) - (x_i - x_{i-1})^2 \frac{\partial}{\partial x} p_i(x_i, y_j)}{p_i^2(x_i, y_j)}.
 \end{aligned}$$

According to (1) of Lemma 2.2 and Lemma 2.1, we derive

$$\begin{aligned} \frac{\partial}{\partial x}R(x_i, y_j) &= \frac{\partial}{\partial x}p_0(x_i, y_j) + \frac{2(x_i - x_0)\varphi_1(x_i, y_j) - (x_i - x_0)^2 \frac{\partial}{\partial x}p_1(x_i, y_j)}{\varphi_1^2(x_i, y_j)} \\ &\quad - (x_i - x_0)^2 \frac{2(x_i - x_1)\varphi_2(x_i, y_j) - (x_i - x_1)^2 \frac{\partial}{\partial x}p_2(x_i, y_j) - \dots}{\varphi_2^2(x_i, y_j)} \\ &\quad - (x_i - x_{i-3})^2 \frac{2(x_i - x_{i-2})\varphi_{i-1}(x_i, y_j) - (x_i - x_{i-2})^2 \frac{\partial}{\partial x}p_{i-1}(x_i, y_j)}{\varphi_{i-1}^2(x_i, y_j)} \\ &\quad - (x_i - x_{i-2})^2 \frac{2(x_i - x_{i-1})\varphi_i(x_i, y_j) - (x_i - x_{i-1})^2 \frac{\partial}{\partial x}\varphi_i(x_i, y_j)}{\varphi_i^2(x_i, y_j)}. \end{aligned}$$

Notice that $\varphi_i(x_i, y_j) = \frac{(x_i - x_{i-1})^2}{\varphi_{i-1}(x_i, y_j) - p_{i-1}(x_i, y_j)}$ and

$$\begin{aligned} \frac{\partial}{\partial x}\varphi_i(x_i, y_j) &= \frac{2(x_i - x_{i-1})(\varphi_{i-1}(x_i, y_j) - p_{i-1}(x_i, y_j))}{(\varphi_{i-1}(x_i, y_j) - p_{i-1}(x_i, y_j))^2} \\ &\quad - \frac{(x_i - x_{i-1})^2 \left(\frac{\partial}{\partial x}\varphi_{i-1}(x_i, y_j) - \frac{\partial}{\partial x}p_{i-1}(x_i, y_j) \right)}{(\varphi_{i-1}(x_i, y_j) - p_{i-1}(x_i, y_j))^2}, \end{aligned}$$

we have

$$\begin{aligned} &\frac{2(x_i - x_{i-1})\varphi_i(x_i, y_j) - (x_i - x_{i-1})^2 \frac{\partial}{\partial x}\varphi_i(x_i, y_j)}{\varphi_i^2(x_i, y_j)} \\ &= \frac{\partial}{\partial x}\varphi_{i-1}(x_i, y_j) - \frac{\partial}{\partial x}p_{i-1}(x_i, y_j). \end{aligned}$$

Consequently,

$$\begin{aligned} \frac{\partial}{\partial x}R(x_i, y_j) &= \frac{\partial}{\partial x}p_0(x_i, y_j) + \frac{2(x_i - x_0)\varphi_1(x_i, y_j) - (x_i - x_0)^2 \frac{\partial}{\partial x}p_1(x_i, y_j) - \dots}{\varphi_1^2(x_i, y_j)} \\ &\quad - (x_i - x_{i-3})^2 \frac{2(x_i - x_{i-2})\varphi_{i-1}(x_i, y_j) - (x_i - x_{i-2})^2 \frac{\partial}{\partial x}\varphi_{i-1}(x_i, y_j)}{\varphi_{i-1}^2(x_i, y_j)}. \end{aligned}$$

By repeating the above procedure, we get

$$\begin{aligned} \frac{\partial}{\partial x}R(x_i, y_j) &= \frac{\partial}{\partial x}p_0(x_i, y_j) + \frac{2(x_i - x_0)\varphi_1(x_i, y_j) - (x_i - x_0)^2 \frac{\partial}{\partial x}\varphi_1(x_i, y_j)}{\varphi_1^2(x_i, y_j)} \\ &= \frac{\partial}{\partial x}p_0(x_i, y_j) + \frac{\partial}{\partial x}\varphi_0(x_i, y_j) - \frac{\partial}{\partial x}p_0(x_i, y_j) = \frac{\partial}{\partial x}\varphi_0(x_i, y_j). \end{aligned}$$

From Step 1 in Algorithm 2.1, we know $\varphi_0(x, y) = f(x, y)$, so

$$\frac{\partial}{\partial x}R(x_i, y_j) = f_x(x_i, y_j), \quad \forall (x_i, y_j) \in \Pi_{x,y}^{n,m}.$$

(c) From (3) of Lemma 2.2, it follows

$$\begin{aligned} \frac{\partial}{\partial y} R(x_i, y_j) &= \frac{\partial}{\partial y} p_0(x_i, y_j) + \frac{-(x_i - x_0)^2 \frac{\partial}{\partial y} p_1(x_i, y_j)}{R_1^2(x_i, y_j)} \\ &+ [-(x_i - x_0)^2] \frac{-(x_i - x_1)^2 \frac{\partial}{\partial y} p_2(x_i, y_j)}{R_2^2(x_i, y_j)} + \dots \\ &+ [-(x_i - x_{i-3})^2] \frac{-(x_i - x_{i-2})^2 \frac{\partial}{\partial y} p_{i-1}(x_i, y_j)}{R_{i-1}^2(x_i, y_j)} \\ &+ [-(x_i - x_{i-2})^2] \frac{-(x_i - x_{i-1})^2 \frac{\partial}{\partial y} p_i(x_i, y_j)}{p_i^2(x_i, y_j)}. \end{aligned}$$

Combining (1) of Lemma 2.2 and Lemma 2.1, we get

$$\begin{aligned} \frac{\partial}{\partial y} R(x_i, y_j) &= \frac{\partial}{\partial y} p_0(x_i, y_j) + \frac{-(x_i - x_0)^2 \frac{\partial}{\partial y} p_1(x_i, y_j)}{\varphi_1^2(x_i, y_j)} \\ &+ [-(x_i - x_0)^2] \frac{-(x_i - x_1)^2 \frac{\partial}{\partial y} p_2(x_i, y_j)}{\varphi_2^2(x_i, y_j)} + \dots \\ &+ [-(x_i - x_{i-3})^2] \frac{-(x_i - x_{i-2})^2 \frac{\partial}{\partial y} p_{i-1}(x_i, y_j)}{\varphi_{i-1}^2(x_i, y_j)} \\ &+ [-(x_i - x_{i-2})^2] \frac{-(x_i - x_{i-1})^2 \frac{\partial}{\partial y} \varphi_i(x_i, y_j)}{\varphi_i^2(x_i, y_j)}. \end{aligned}$$

Notice that

$$\begin{aligned} \varphi_i(x_i, y_j) &= \frac{(x_i - x_{i-1})^2}{\varphi_{i-1}(x_i, y_j) - p_{i-1}(x_i, y_j)}, \\ \frac{\partial}{\partial y} \varphi_i(x_i, y_j) &= \frac{-(x_i - x_{i-1})^2 \left(\frac{\partial}{\partial y} \varphi_{i-1}(x_i, y_j) - \frac{\partial}{\partial y} p_{i-1}(x_i, y_j) \right)}{(\varphi_{i-1}(x_i, y_j) - p_{i-1}(x_i, y_j))^2}. \end{aligned}$$

Consequently,

$$\frac{-(x_i - x_{i-1})^2 \frac{\partial}{\partial y} \varphi_i(x_i, y_j)}{\varphi_i^2(x_i, y_j)} = \frac{\partial}{\partial y} \varphi_{i-1}(x_i, y_j) - \frac{\partial}{\partial y} p_{i-1}(x_i, y_j).$$

We then have

$$\begin{aligned} \frac{\partial}{\partial y}R(x_i, y_j) &= \frac{\partial}{\partial y}p_0(x_i, y_j) + \frac{-(x_i - x_0)^2 \frac{\partial}{\partial y}p_1(x_i, y_j)}{\varphi_1^2(x_i, y_j)} \\ &\quad + [- (x_i - x_0)^2] \frac{-(x_i - x_1)^2 \frac{\partial}{\partial y}p_2(x_i, y_j)}{\varphi_2^2(x_i, y_j)} \\ &\quad + \dots + [- (x_i - x_{i-3})^2] \frac{-(x_i - x_{i-2})^2 \frac{\partial}{\partial y}\varphi_{i-1}(x_i, y_j)}{\varphi_{i-1}^2(x_i, y_j)} \\ &= \dots \\ &= \frac{\partial}{\partial y}p_0(x_i, y_j) + \frac{-(x_i - x_0)^2 \frac{\partial}{\partial y}\varphi_1(x_i, y_j)}{\varphi_1^2(x_i, y_j)} \\ &= \frac{\partial}{\partial y}p_0(x_i, y_j) + \frac{\partial}{\partial y}\varphi_0(x_i, y_j) - \frac{\partial}{\partial y}p_0(x_i, y_j) \\ &= \frac{\partial}{\partial y}\varphi_0(x_i, y_j). \end{aligned}$$

From Step 1 in Algorithm 2.1, we know $\varphi_0(x, y) = f(x, y)$. Therefore, $\frac{\partial}{\partial y}R(x_i, y_j) = f_y(x_i, y_j), \forall (x_i, y_j) \in \Pi_{x,y}^{n,m}$. So the proof of Theorem 2.1 is complete. ■

3. Characteristic properties of TWBORIs

For brevity, we cite the bivariate blending osculatory rational interpolation defined by (2.9) as TWBORIs.

Theorem 3.1. *Let $R(x, y)$ be a bivariate blending osculatory rational interpolation as in (2.9), and assume that every $p_0(x, y), p_1(x, y), \dots, p_n(x, y)$ defined in Algorithm 2.1 exists, with a tail-to-head rationalize evaluation for $R(x, y)$. Then polynomials $N(x, y)$ and $D(x, y)$ exist and satisfy*

$$(i). R(x, y) = \frac{N(x, y)}{D(x, y)}, \quad D(x, y) \geq 0; \quad (ii). D(x, y) | N^2(x, y).$$

Proof. Let $R_s(x, y)$ and $R(x, y)$ be defined by (2.8) and (2.9) respectively. For $s = n$,

$$R_n(x, y) = p_n(x, y) = \frac{N_n(x, y)}{D_n(x, y)},$$

which gives

$$D_n(x, y) \geq 0, \quad D_n(x, y) | N_n^2(x, y).$$

Therefore, the conclusion of Theorem 3.1 holds true for $s = n$. Now, assume

$$R_k(x, y) = \frac{N_k(x, y)}{D_k(x, y)}, \quad D_k(x, y) \geq 0, \quad D_k(x, y) | N_k^2(x, y) \text{ valid for } s = k.$$

Then for $s = k - 1$,

$$\begin{aligned} R_{k-1}(x, y) &= p_{k-1}(x, y) + \frac{(x - x_{k-1})^2}{R_k(x, y)} = p_{k-1}(x, y) + \frac{(x - x_{k-1})^2 D_k(x, y)}{N_k(x, y)} \\ &= \frac{p_{k-1}(x, y) \frac{N_k^2(x, y)}{D_k(x, y)} + (x - x_{k-1})^2 N_k(x, y)}{\frac{N_k^2(x, y)}{D_k(x, y)}}. \end{aligned}$$

Let

$$D_{k-1}(x, y) = \frac{N_k^2(x, y)}{D_k(x, y)}, \quad N_{k-1}(x, y) = p_{k-1}(x, y) D_{k-1}(x, y) + (x - x_{k-1})^2 N_k(x, y).$$

Thus

$$R_{k-1}(x, y) = \frac{N_{k-1}(x, y)}{D_{k-1}(x, y)}, \quad D_{k-1}(x, y) \geq 0$$

and

$$\begin{aligned} N_{k-1}^2(x, y) &= p_{k-1}^2(x, y) D_{k-1}^2(x, y) + 2p_{k-1}(x, y) D_{k-1}(x, y) (x - x_{k-1})^2 N_k(x, y) \\ &\quad + (x - x_{k-1})^4 N_k^2(x, y), \\ D_{k-1}(x, y) &= \frac{N_k^2(x, y)}{D_k(x, y)}. \end{aligned}$$

Consequently,

$$D_{k-1}(x, y) | N_{k-1}^2(x, y).$$

Choosing $k = 1$, Theorem 3.1 is proved by induction. ■

Suppose $f(x, y)$ is a bivariate polynomial. We denote by $\partial_x f$ the degree of $f(x, y)$ with respect to variable x and by $\partial_y f$ the degree of $f(x, y)$ with respect to variable y [3].

Theorem 3.2. *The interpolating rational function $R(x, y)$ given in (2.9) is of degree $(n+1/n)$ with respect to x and $((n+1)(2m+1)/n(2m+1))$ with respect to y .*

Proof. It is easy to observe from (2.4)

$$\partial_x p_s(x, y) = 1, \quad \partial_y p_s(x, y) = 2m + 1, \quad s = 0, 1, \dots, n.$$

We denote by

$$R^{(s)}(x, y) = p_0(x, y) + \frac{(x - x_0)^2}{p_1(x, y)} + \frac{(x - x_1)^2}{p_2(x, y)} + \dots + \frac{(x - x_{s-1})^2}{p_s(x, y)} = \frac{N^{(s)}(x, y)}{D^{(s)}(x, y)}.$$

For $s = 0$,

$$R^{(0)}(x, y) = p_0(x, y) = \frac{N^{(0)}(x, y)}{D^{(0)}(x, y)},$$

which gives

$$\partial_x N^{(0)}(x, y) = 1, \quad \partial_x D^{(0)}(x, y) = 0, \quad \partial_y N^{(0)}(x, y) = 2m + 1, \quad \partial_y D^{(0)}(x, y) = 0.$$

For $s = 1$,

$$R^{(1)}(x, y) = p_0(x, y) + \frac{(x - x_0)^2}{p_1(x, y)} = \frac{p_0(x, y)p_1(x, y) + (x - x_0)^2}{p_1(x, y)} = \frac{N^{(1)}(x, y)}{D^{(1)}(x, y)},$$

thus

$$\partial_x N^{(1)}(x, y) = 2, \quad \partial_x D^{(1)}(x, y) = 1, \quad \partial_y N^{(1)}(x, y) = 4m + 2, \quad \partial_y D^{(1)}(x, y) = 2m + 1.$$

Now we assume that

$$\begin{aligned} \partial_x N^{(s)}(x, y) &= s + 1, & \partial_x D^{(s)}(x, y) &= s, \\ \partial_y N^{(s)}(x, y) &= (s + 1)(2m + 1), & \partial_y D^{(s)}(x, y) &= s(2m + 1). \end{aligned}$$

Then by the three-term recurrence formula, we get

$$\begin{aligned} N^{(s+1)}(x, y) &= p_{s+1}(x, y)N^{(s)}(x, y) + (x - x_s)^2 N^{(s-1)}(x, y), \\ D^{(s+1)}(x, y) &= p_{s+1}(x, y)D^{(s)}(x, y) + (x - x_s)^2 D^{(s-1)}(x, y). \end{aligned}$$

According to the hypothesis, it follows

$$\begin{aligned} \partial_x N^{(s+1)}(x, y) &= \max\{1 + s + 1, 2 + s + 1 - 1\} = s + 2, \\ \partial_y N^{(s+1)}(x, y) &= \max\{2m + 1 + (s + 1)(2m + 1), (s + 1 - 1)(2m + 1)\} \\ &= (2m + 1)(s + 2), \\ \partial_x D^{(s+1)}(x, y) &= \max\{1 + s + 1 - 1, 2 + s + 1 - 2\} = s + 1, \\ \partial_y D^{(s+1)}(x, y) &= \max\{2m + 1 + (s + 1 - 1)(2m + 1), (s + 1 - 2)(2m + 1)\} \\ &= (s + 1)(2m + 1). \end{aligned}$$

Therefore, the proof of Theorem 3.2 is completed by induction. ■

4. Error estimation

Let

$$R^*(x, y) = p_0^*(x, y) + \frac{(x - x_0)^2}{p_1^*(x, y)} + \cdots + \frac{(x - x_{n-1})^2}{p_n^*(x, y)} = \frac{N^*(x, y)}{D^*(x, y)}, \quad (4.1)$$

$$\begin{aligned} p_i^*(x, y) = & \varphi_i^*(x_i, y_0) + \varphi_i^*[x_i; y_0, y_0](y - y_0) + \varphi_i^*[x_i; y_0, y_0, y_1](y - y_0)^2 \\ & + \cdots + \varphi_i^*[x_i; y_0, y_0, \dots, y_m, y_m](y - y_0)^2 \cdots (y - y_{m-1})^2 (y - y_m) \\ & + \varphi_i^*[x_i; y_0, y_0, \dots, y_m, y_m, y](y - y_0)^2 \cdots (y - y_m)^2 \\ & + (x - x_i)(\varphi_i^*[x_i, x_i; y_0] + \varphi_i^*[x_i, x_i; y_0, y_1](y - y_0) \\ & + \cdots + \varphi_i^*[x_i, x_i; y_0, \dots, y_m](y - y_0) \cdots (y - y_{m-1}) \\ & + \varphi_i^*[x_i, x_i; y_0, \dots, y_m, y](y - y_0) \cdots (y - y_m)), \end{aligned} \quad (4.2)$$

$$\varphi_i^*(x, y) = \frac{(x - x_{i-1})^2}{\varphi_{i-1}^*(x, y) - p_{i-1}^*(x, y)}, \quad i = 1, \dots, n. \quad (4.3)$$

Especially, let $\varphi_0^*(x, y) = \varphi_0(x, y) = f(x, y)$.

Lemma 4.1. *Suppose every $p_i^*(x, y)$ in (4.2) exists. Then $R^*(x, y)$ defined in (4.1) satisfies:*

$$(1) \quad R^*(x_i, y) = f(x_i, y), \quad \frac{\partial}{\partial x} R^*(x_i, y) = f_x(x_i, y), \quad i = 0, 1, \dots, n.$$

$$(2) \quad R^*(x, y_j) = R(x, y_j), \quad j = 0, 1, \dots, m.$$

Proof.

(1). (i) From (4.2), we have

$$\begin{aligned} p_i^*(x_i, y) = & \varphi_i^*(x_i, y_0) + \varphi_i^*[x_i; y_0, y_0](y - y_0) + \varphi_i^*[x_i; y_0, y_0, y_1](y - y_0)^2 \\ & + \cdots + \varphi_i^*[x_i; y_0, y_0, \dots, y_m, y_m](y - y_0)^2 \cdots (y - y_{m-1})^2 (y - y_m) \\ & + \varphi_i^*[x_i; y_0, y_0, \dots, y_m, y_m, y](y - y_0)^2 \cdots (y - y_m)^2. \end{aligned}$$

By Definition 2.1, it follows

$$p_i^*(x_i, y) = \varphi_i^*(x_i, y), \quad i = 0, 1, \dots, n. \quad (4.4)$$

Let

$$R_s^*(x, y) = p_s^*(x, y) + \frac{(x - x_s)^2}{p_{s+1}^*(x, y)} + \frac{(x - x_{s+1})^2}{p_{s+2}^*(x, y)} + \cdots + \frac{(x - x_{n-1})^2}{p_n^*(x, y)},$$

for $s = 0, 1, \dots, n, t = s, s + 1, \dots, n$. According to (4.3) and (4.4), we derive

$$\begin{aligned} R_s^*(x_t, y) &= p_s^*(x_t, y) + \frac{(x_t - x_s)^2}{p_{s+1}^*(x_t, y)} + \dots + \frac{(x_t - x_{t-1})^2}{p_t^*(x_t, y)} \\ &= p_s^*(x_t, y) + \frac{(x_t - x_s)^2}{p_{s+1}^*(x_t, y)} + \dots + \frac{(x_t - x_{t-1})^2}{\varphi_t^*(x_t, y)} \\ &= p_s^*(x_t, y) + \frac{(x_t - x_s)^2}{p_{s+1}^*(x_t, y)} + \dots + \frac{(x_t - x_{t-1})^2}{\frac{(x_t - x_{t-1})^2}{\varphi_{t-1}^*(x_t, y) - p_{t-1}^*(x_t, y)}} \\ &= \dots = \varphi_s^*(x_t, y). \end{aligned}$$

Consequently,

$$R_s^*(x_t, y) = \varphi_s^*(x_t, y), \quad s = 0, 1, \dots, n, \quad t = s, s + 1, \dots, n. \tag{4.5}$$

Choosing $s = 0$, we get $R^*(x_i, y) = \varphi_0^*(x_i, y) = f(x_i, y)$.

(ii) From (2) of Lemma 2.2, it follows

$$\begin{aligned} \frac{\partial}{\partial x} R^*(x_i, y) &= \frac{\partial}{\partial x} p_0^*(x_i, y) + \frac{2(x_i - x_0)R_1^*(x_i, y) - (x_i - x_0)^2 \frac{\partial}{\partial x} p_1^*(x_i, y)}{R_1^{*2}(x_i, y)} \\ &\quad - (x_i - x_0)^2 \frac{2(x_i - x_1)R_2^*(x_i, y) - (x_i - x_1)^2 \frac{\partial}{\partial x} p_2^*(x_i, y) - \dots}{R_2^{*2}(x_i, y)} \\ &\quad - (x_i - x_{i-2})^2 \frac{2(x_i - x_{i-1})p_i^*(x_i, y) - (x_i - x_{i-1})^2 \frac{\partial}{\partial x} p_i^*(x_i, y)}{p_i^{*2}(x_i, y)}. \end{aligned} \tag{4.6}$$

We get from (4.2),

$$\frac{\partial}{\partial x} p_i^*(x_i, y) = \varphi_i^*[x_i, x_i; y] = \frac{\partial}{\partial x} \varphi_i^*(x_i, y). \tag{4.7}$$

Combining (4.3)-(4.7) and using the similar method used in the proof of (b) in Theorem 2.1, we conclude that

$$\frac{\partial}{\partial x} R^*(x_i, y) = \frac{\partial}{\partial x} \varphi_0^*(x_i, y) = f_x(x_i, y)$$

holds for $i = 0, 1, \dots, n$.

(2). It can be verified that

$$R(x, y_j) = p_0(x, y_j) + \frac{(x - x_0)^2}{p_1(x, y_j)} + \frac{(x - x_1)^2}{p_2(x, y_j)} + \cdots + \frac{(x - x_{n-1})^2}{p_n(x, y_j)}, \quad (4.8)$$

$$R^*(x, y_j) = p_0^*(x, y_j) + \frac{(x - x_0)^2}{p_1^*(x, y_j)} + \frac{(x - x_1)^2}{p_2^*(x, y_j)} + \cdots + \frac{(x - x_{n-1})^2}{p_n^*(x, y_j)}, \quad (4.9)$$

$$\begin{aligned} p_i(x, y_j) &= \varphi_i(x_i, y_j) + (x - x_i)\varphi_i[x_i, x_i; y_j] \\ &= \varphi_i(x_i, y_j) + (x - x_i)\frac{\partial}{\partial x}\varphi_i(x_i, y_j), \end{aligned} \quad (4.10)$$

$$\begin{aligned} p_i^*(x, y_j) &= \varphi_i^*(x_i, y_j) + (x - x_i)\varphi_i^*[x_i, x_i; y_j] \\ &= \varphi_i^*(x_i, y_j) + (x - x_i)\frac{\partial}{\partial x}\varphi_i^*(x_i, y_j). \end{aligned} \quad (4.11)$$

For $\varphi_0^*(x, y) = \varphi_0(x, y)$, $p_0(x, y_j) = p_0^*(x, y_j)$. For

$$\varphi_1^*(x, y_j) = \frac{(x - x_0)^2}{\varphi_0^*(x, y_j) - p_0^*(x, y_j)} = \frac{(x - x_0)^2}{\varphi_0(x, y_j) - p_0(x, y_j)} = \varphi_1(x, y_j),$$

so

$$\frac{\partial}{\partial x}\varphi_1^*(x, y_j) = \frac{\partial}{\partial x}\varphi_1(x, y_j).$$

According to (4.10) and (4.11), we have $p_1(x, y_j) = p_1^*(x, y_j)$. Similarly, we get

$$p_i(x, y_j) = p_i^*(x, y_j), \quad i = 0, 1, \dots, n, \quad j = 0, 1, \dots, m,$$

by (4.8) and (4.9). Thus $R(x, y_j) = R^*(x, y_j)$ holds for $j = 0, 1, \dots, m$.

Theorem 4.1. (Error estimation) Suppose $D = [a, b] \times [c, d]$, $X_n = \{x_0, x_1, \dots, x_n\} \subset [a, b] \subset \mathbb{R}$, $Y_m = \{y_0, y_1, \dots, y_m\} \subset [c, d] \subset \mathbb{R}$, $\Pi_{x,y}^{n,m} = X_n \times Y_m$, and $f(x, y) \in C^{2n+m+3}(D)$. Let $R(x, y), R^*(x, y), N(x, y), D(x, y), N^*(x, y)$ and $D^*(x, y)$ be defined in Theorem 3.1 and (4.1) respectively. Let

$$\begin{aligned} E(x, y) &= D(x, y)D^*(x, y)(f(x, y) - R(x, y)), \\ u_n(x) &= (x - x_0)(x - x_1) \cdots (x - x_n), \\ v_m(y) &= (y - y_0)(y - y_1) \cdots (y - y_m). \end{aligned}$$

Then

$$\begin{aligned} E(x, y) &= \frac{u_n^2(x)}{(2n + 2)!} \frac{\partial^{2n+2} E(\xi, y)}{\partial x^{2n+2}} + \frac{v_m(y)}{(m + 1)!} \frac{\partial^{m+1} E(x, \eta)}{\partial y^{m+1}} \\ &\quad - \frac{u_n^2(x)}{(2n + 2)!} \frac{v_m(y)}{(m + 1)!} \frac{\partial^{2n+m+3} E(\xi, \eta)}{\partial x^{2n+2} \partial y^{m+1}}, \end{aligned}$$

where $\xi \in (a, b)$ and $\eta \in (c, d)$.

Proof. Let

$$\begin{aligned} E_1(x, y) &= D(x, y)D^*(x, y)(f(x, y) - R^*(x, y)), \\ E_2(x, y) &= D(x, y)D^*(x, y)(R^*(x, y) - R(x, y)). \end{aligned}$$

By (1) of Lemma 4.1, we have $E_1(x_i, y) = 0$, $\frac{\partial}{\partial x}E_1(x_i, y) = 0$. Consequently,

$$E_1(x, y) = \frac{u_n^2(x)}{(2n+2)!} \frac{\partial^{2n+2}E_1(\xi, y)}{\partial x^{2n+2}}, \tag{4.12}$$

where $u_n(x) = (x - x_0)(x - x_1) \cdots (x - x_n)$, ξ is located among x_0, x_1, \dots, x_n, x .

From (2) of Lemma 4.1, it follows $E_2(x, y_j) = 0$, $j = 0, 1, \dots, m$. So

$$E_2(x, y) = \frac{v_m(y)}{(m+1)!} \frac{\partial^{m+1}E_2(x, \eta)}{\partial y^{m+1}}, \tag{4.13}$$

where $v_m(y) = (y - y_0)(y - y_1) \cdots (y - y_m)$, η is located among y_0, y_1, \dots, y_m, y . Notice that

$$\begin{aligned} E_2(x, y) &= D(x, y)D^*(x, y)(R^*(x, y) - R(x, y)) \\ &= D(x, y)N^*(x, y) - D^*(x, y)N(x, y). \end{aligned}$$

Hence,

$$\partial_x E_2(x, y) = \max\{2n+1, 2n+1\} = 2n+1,$$

which gives

$$\frac{\partial^{2n+2}E(x, y)}{\partial x^{2n+2}} = \frac{\partial^{2n+2}E_1(x, y)}{\partial x^{2n+2}}. \tag{4.14}$$

Combining (4.12)-(4.14), we derive

$$\begin{aligned} E(x, y) &= E_1(x, y) + E_2(x, y) \\ &= \frac{u_n^2(x)}{(2n+2)!} \frac{\partial^{2n+2}E_1(\xi, y)}{\partial x^{2n+2}} + \frac{v_m(y)}{(m+1)!} \frac{\partial^{m+1}E_2(x, \eta)}{\partial y^{m+1}} \\ &= \frac{u_n^2(x)}{(2n+2)!} \frac{\partial^{2n+2}E(\xi, y)}{\partial x^{2n+2}} + \frac{v_m(y)}{(m+1)!} \frac{\partial^{m+1}(E(x, \eta) - E_1(x, \eta))}{\partial y^{m+1}} \\ &= \frac{u_n^2(x)}{(2n+2)!} \frac{\partial^{2n+2}E(\xi, y)}{\partial x^{2n+2}} + \frac{v_m(y)}{(m+1)!} \frac{\partial^{m+1}E(x, \eta)}{\partial y^{m+1}} \\ &\quad - \frac{v_m(y)}{(m+1)!} \frac{\partial^{m+1}}{\partial y^{m+1}} \left[\frac{u_n^2(x)}{(2n+2)!} \frac{\partial^{2n+2}E_1(\xi, \eta)}{\partial x^{2n+2}} \right] \\ &= \frac{u_n^2(x)}{(2n+2)!} \frac{\partial^{2n+2}E(\xi, y)}{\partial x^{2n+2}} + \frac{v_m(y)}{(m+1)!} \frac{\partial^{m+1}E(x, \eta)}{\partial y^{m+1}} \\ &\quad - \frac{u_n^2(x)}{(2n+2)!} \frac{v_m(y)}{(m+1)!} \frac{\partial^{2n+m+3}E(\xi, \eta)}{\partial x^{2n+2} \partial y^{m+1}}. \blacksquare \end{aligned}$$

Table 5.1: Data sets.

| | | | | |
|-----------|--------------------------|--------------------------|--------------------------|-------------------------|
| | $x_0 = 2$ | $x_0 = 2$ | $x_1 = 3$ | $x_1 = 3$ |
| $y_0 = 2$ | $f(x_0, y_0) = 1.5$ | $f_x(x_0, y_0) = 0.9375$ | $f(x_1, y_0) = 2.8182$ | $f_x(x_1, y_0) = 1.686$ |
| $y_0 = 2$ | $f_y(x_0, y_0) = 0.3125$ | | $f_y(x_1, y_0) = 0.1074$ | |
| $y_1 = 3$ | $f(x_0, y_1) = 1.8889$ | $f_x(x_0, y_1) = 0.7037$ | $f(x_1, y_1) = 3$ | $f_x(x_1, y_1) = 1.5$ |
| $y_1 = 3$ | $f_y(x_0, y_1) = 0.4568$ | | $f_y(x_1, y_1) = 0.25$ | |

5. Numerical example

Example 5.1. Suppose $(x_i, y_j), f(x_i, y_j), f_x(x_i, y_j)$ and $f_y(x_i, y_j)$ are given in the Table 5.1. Let $\varphi_0(x, y) = f(x, y)$. We want to find a polynomial $p_0(x, y)$, such that

| | | |
|-----------|--|--|
| | $x_0 = 2$ | $x_0 = 2$ |
| $y_0 = 2$ | $p_0(2, 2) = \varphi_0(2, 2) = 1.5$ | $\frac{\partial}{\partial x} p_0(2, 2) = \frac{\partial}{\partial x} \varphi_0(2, 2) = 0.9375$ |
| $y_0 = 2$ | $\frac{\partial}{\partial y} p_0(2, 2) = \frac{\partial}{\partial y} \varphi_0(2, 2) = 0.3125$ | |
| $y_1 = 3$ | $p_0(2, 3) = \varphi_0(2, 3) = 1.8889$ | $\frac{\partial}{\partial x} p_0(2, 3) = \frac{\partial}{\partial x} \varphi_0(2, 3) = 0.7037$ |
| $y_1 = 3$ | $\frac{\partial}{\partial y} p_0(2, 3) = \frac{\partial}{\partial y} \varphi_0(2, 3) = 0.4568$ | |

Using Step 1 in Algorithm 2.1 gives

$$p_0(x, y) = \frac{7}{8} + \frac{5}{16}y + \frac{191}{2500}(y - 2)^2 + \left(-\frac{19140298416325}{2251799813685248}y + \frac{57420895248975}{2251799813685248} \right) (y - 2)^2 + (x - 2) \left(\frac{14051}{10000} - \frac{1169}{5000}y \right).$$

Let $\varphi_1(x, y) = \frac{(x-2)^2}{\varphi_0(x, y) - p_0(x, y)}$. We wish to find a polynomial $p_1(x, y)$, such that

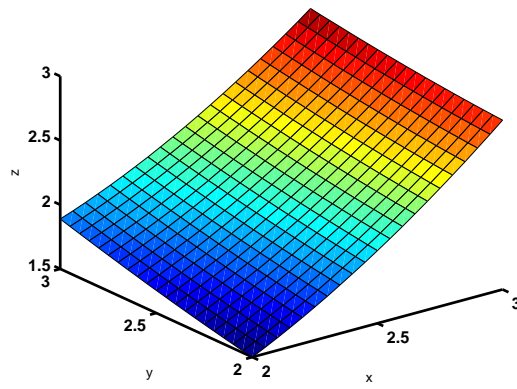
| | | |
|-----------|---|--|
| | $x_1 = 3$ | $x_1 = 3$ |
| $y_0 = 2$ | $p_1(3, 2) = \varphi_1(3, 2) = 2.6269$ | $\frac{\partial}{\partial x} p_1(3, 2) = \frac{\partial}{\partial x} \varphi_1(3, 2) = 0.0891$ |
| $y_0 = 2$ | $\frac{\partial}{\partial y} p_1(3, 2) = \frac{\partial}{\partial y} \varphi_1(3, 2) = -0.1983$ | |
| $y_1 = 3$ | $p_1(3, 3) = \varphi_1(3, 3) = 2.4546$ | $\frac{\partial}{\partial x} p_1(3, 3) = \frac{\partial}{\partial x} \varphi_1(3, 3) = 0.1115$ |
| $y_1 = 3$ | $\frac{\partial}{\partial y} p_1(3, 3) = \frac{\partial}{\partial y} \varphi_1(3, 3) = -0.1627$ | |

Using Step 2 in Algorithm 2.1 gives

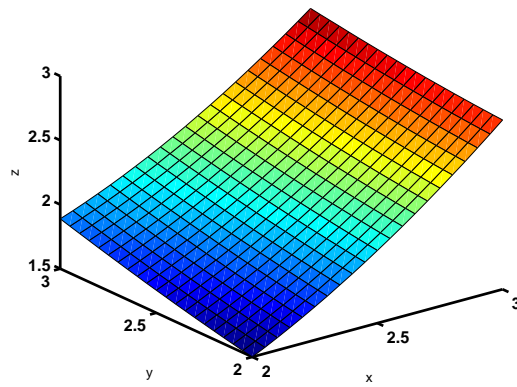
$$p_1(x, y) = \frac{6047}{2000} - \frac{1983}{10000}y + \frac{936748722493067}{36028797018963968}(y - 2)^2 + \left(-\frac{590872271111019}{36028797018963968}y + \frac{1772616813333057}{36028797018963968} \right) (y - 2)^2 + (x - 3) \left(\frac{443}{10000} + \frac{14}{625}y \right).$$

Therefore $R(x, y) = p_0(x, y) + \frac{(x-2)^2}{p_1(x, y)}$.

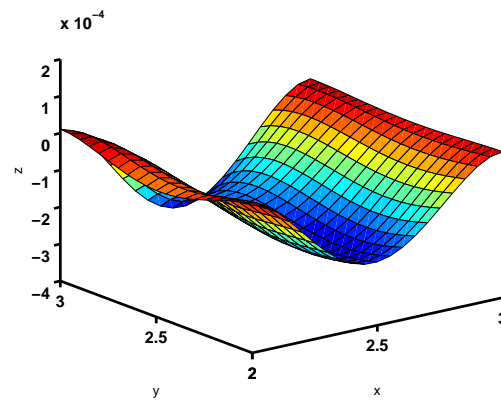
In Fig. 5.1, the interpolation function $R(x, y)$ and the corresponding error function are plotted. It is seen that the error is small, which implies that the proposed algorithm is efficient.



(a)



(b)



(c)

Fig. 5.1. (a) $f(x, y) = \frac{x^3+y^2}{3x+y}$. (b) Interpolating function $R(x, y)$. (c) Error function.

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References

- [1] Graves-Morris P R. Efficient reliable rational interpolation. In *Padé Approximation and its Applications*, Lecture Notes in Math. 888, van Rossum H, de Bruin M (Eds.), Springer, Berlin, 1981, pp. 28-63.
- [2] Graves-Morris P R. Vector valued rational interpolants I. *Numer. Math.*, 1983, 42: 331-348.
- [3] Tan J Q. Bivariate blending rational interpolants. *Approx. Theory Appl.*, 1999, 15(2): 74-83.
- [4] Tan J Q, Tang S. Composite schemes for multivariate blending rational interpolants. *J. Comput. Appl. Math.*, 2002, 144: 263-275.
- [5] Tang S, Sheng M. A scheme for bivariate blending osculatory rational interpolation. *J. Inform. Comput. Sci.*, 2005, 2: 789-798.
- [6] Wang R H, Zhu G Q. *The Approximation of Rational Functions and Applications*, Science Press, Beijing, 2004 (in Chinese).
- [7] Werner H. A reliable method for rational interpolation. In *Padé Approximation and its Applications*, Wuytack L (Ed.), Springer, Berlin, 1979, pp. 257-277.