



2.1 Runge-Kutta 方法的构造思想

由

$$y(x_{i+1}) = y(x_i) + \int_{x_i}^{x_{i+1}} f(x, y(x)) dx$$

可以得到

$$y(x_{i+1}) = y(x_i) + hf(x_i + \theta h, y(x_i + \theta h)),$$

称 $f(x_i + \theta h, y(x_i + \theta h))$ 为 $y(x)$ 在 $[x_i, x_{i+1}]$ 上的平均斜率, 记为 k^* .
记

$$k_1 = f(x_i, y_i), \quad k_2 = f(x_{i+1}, y_i + hk_1),$$

若用 k_1 近似 k^* , 则得一阶 Euler 公式, 若用 $\frac{k_1+k_2}{2}$ 近似 k^* , 则得 2 阶改进的 Euler 公式.



一般的 r 级 Runge-Kutta 方法为

$$\begin{cases} y_{i+1} = y_i + h \sum_{j=1}^r \alpha_j k_j, \\ k_1 = f(x_i, y_i), \\ k_j = f\left(x_i + \lambda_j h, y_i + h \sum_{l=1}^{j-1} \mu_{jl} k_l\right), \quad j = 2, 3, \dots, r. \end{cases} \quad (2.1)$$

选择参数 $\alpha_j, \lambda_j, \mu_{jl}$ 使其具有一定的阶数. 具体将局部截断误差

$$R_{i+1} = y(x_{i+1}) - y(x_i) - h \sum_{j=1}^r \alpha_j K_j,$$

其中

$$\begin{aligned} K_1 &= f(x_i, y(x_i)), \\ K_j &= f\left(x_i + \lambda_j h, y(x_i) + h \sum_{l=1}^{j-1} \mu_{jl} K_l\right), \quad j = 2, 3, \dots, r, \end{aligned}$$



展开为 h 的幂级数

$$R_{i+1} = c_0 + c_1 h + \cdots + c_p h^p + c_{p+1} h^{p+1} + \cdots$$

选择参数 $\alpha_j, \lambda_j, \mu_{jl}$, 使得 $c_0 = c_1 = \cdots = c_p = 0$, 而 $c_{p+1} \neq 0$, 则公式 (2.1) 是 p 阶的.



2.2 2 阶 Runge-Kutta 公式

2 阶 Runge-Kutta 公式一般形式为

$$\begin{cases} y_{i+1} = y_i + h(\alpha_1 k_1 + \alpha_2 k_2) \\ k_1 = f(x_i, y_i) \\ k_2 = f(x_i + \lambda_2 h, y_i + h\mu_{21} k_1) \end{cases} . \quad (2.2)$$

其局部截断误差是

$$\begin{cases} R_{i+1} = y(x_{i+1}) - y(x_i) - h(\alpha_1 K_1 + \alpha_2 K_2) \\ K_1 = f(x_i, y(x_i)) \\ K_2 = f(x_i + \lambda_2 h, y(x_i) + h\mu_{21} K_1) \end{cases}$$

$$\begin{aligned}
 y(x_{i+1}) &= y(x_i) + hy'(x_i) + \frac{1}{2}h^2 y''(x_i) + \frac{1}{3!}h^3 y'''(x_i) + O(h^4) \\
 &= y(x_i) + hy'(x_i) + \frac{1}{2}h^2 \left[\frac{\partial f}{\partial x}(x_i, y(x_i)) + y'(x_i) \frac{\partial f}{\partial y}(x_i, y(x_i)) \right] + \frac{h^3}{6} y'''(x_i) + O(h^4)
 \end{aligned}$$

$$K_1 = y'(x_i),$$

$$\begin{aligned}
 K_2 &= f(x_i, y(x_i)) + \lambda_2 h \frac{\partial f}{\partial x}(x_i, y(x_i)) + h\mu_{21} y'(x_i) \frac{\partial f}{\partial y}(x_i, y(x_i)) \\
 &\quad + \frac{1}{2} \left[(\lambda_2 h)^2 \frac{\partial^2 f}{\partial x^2}(x_i, y(x_i)) + 2\lambda_2 \mu_{21} h^2 y'(x_i) \frac{\partial^2 f}{\partial y^2}(x_i, y(x_i)) \right. \\
 &\quad \left. + (\mu_{21} h y'(x_i))^2 \frac{\partial^2 f}{\partial y^2}(x_i, y(x_i)) \right] + O(h^3)
 \end{aligned}$$



将上面 3 式代入局部截断误差得

$$\begin{aligned} R_{i+1} = & h(1 - \alpha_1 - \alpha_2)y'(x_i) \\ & + h^2 \left[\left(\frac{1}{2} - \alpha_2\lambda_2 \right) \frac{\partial f}{\partial x}(x_i, y(x_i)) + \left(\frac{1}{2} - \alpha_2\mu_{21} \right) y'(x_i) \frac{\partial f}{\partial y}(x_i, y(x_i)) \right] \\ & + h^3 \left[\frac{1}{6} y'''(x_i) - \frac{1}{2} \alpha_2 \left((\lambda_2)^2 \frac{\partial^2 f}{\partial x^2}(x_i, y(x_i)) + 2\lambda_2\mu_{21} y'(x_i) \frac{\partial^2 f}{\partial x \partial y}(x_i, y(x_i)) \right. \right. \\ & \left. \left. + (\mu_{21} y'(x_i))^2 \frac{\partial^2 f}{\partial y^2}(x_i, y(x_i)) \right) \right] + O(h^4). \end{aligned}$$



要使 (2.2) 具有 2 阶精度, 则

$$\begin{cases} 1 - \alpha_1 - \alpha_2 = 0, \\ \frac{1}{2} - \alpha_2 \lambda_2 = 0, \\ \frac{1}{2} - \alpha_2 \mu_{21} = 0. \end{cases}$$

显然 α_2 不能为零. 当 $\alpha_2 \neq 0$, 可得

$$\begin{cases} \alpha_1 = 1 - \alpha_2, \\ \lambda_2 = \frac{1}{2\alpha_2}, \\ \mu_{21} = \frac{1}{2\alpha_2}. \end{cases}$$



于是我们可以得到一类 2 阶 Runge-Kutta 公式

$$\begin{cases} y_{i+1} = y_i + h[(1 - \alpha_2)k_1 + \alpha_2 k_2], \\ k_1 = f(x_i, y_i), \\ k_2 = f\left(x_i + \frac{1}{2\alpha_2}h, y_i + \frac{1}{2\alpha_2}hk_1\right). \end{cases}$$

当 $\alpha_2 = \frac{1}{2}$, 得改进的 Euler 公式. 当 $\alpha_2 = 1$, 得变形的 Euler 公式:

$$\begin{cases} y_{i+1} = y_i + hk_2, \\ k_1 = f(x_i, y_i), \\ k_2 = f\left(x_i + \frac{1}{2}h, y_i + \frac{1}{2}hk_1\right). \end{cases}$$



若 $\alpha_2 = \frac{3}{4}$, 则得

$$\begin{cases} y_{i+1} = y_i + \frac{h}{4}(k_1 + 3k_2), \\ k_1 = f(x_i, y_i), \\ k_2 = f\left(x_i + \frac{2}{3}h, y_i + \frac{2}{3}hk_1\right). \end{cases}$$

利用上述构造方法可以得到 3 阶或 4 阶等高阶 Runge-Kutta 公式.



3.1 收敛性

考虑单步显式公式

$$\begin{cases} y_{i+1} = y_i + h\varphi(x_i, y_i, h), & i = 0, 1, \dots, n-1, \\ y_0 = \eta. \end{cases} \quad (3.1)$$

定理 3.1

设 $y(x)$ 是微分方程 (0.1) 的解, $\{y_i\}_{i=0}^n$ 为单步显式公式 (3.1) 的解. 如果

- ① 存在常数 $c_0 > 0$, 使得 $|R_{i+1}| \leq c_0 h^{p+1}$, $i = 0, 1, \dots, n-1$,
- ② 存在 $h_0 > 0$, $L > 0$, 使得 $\max_{\substack{(x,y) \in D_\delta \\ 0 \leq h \leq h_0}} \left| \frac{\partial \varphi(x,y,h)}{\partial y} \right| \leq L$.

则当 $h \leq \min \left\{ h_0, \sqrt[p]{\frac{\delta}{c}} \right\}$ 时, 有

$$E(h) \leq ch^p.$$

其中 $D_\delta = \{(x, y) \mid a \leq x \leq b, y(x) - \delta \leq y \leq y(x) + \delta\}$, $c = \frac{c_0}{L} [e^{L(b-a)} - 1]$.



3.2 稳定性

定义 3.1

对于初值问题 (0.1), 设 $\{y_i\}_{i=0}^n$ 是由单步法 (3.1) 得到的近似解, $\{z_i\}_{i=0}^n$ 是 (3.1) 扰动后的解, 即满足

$$\begin{cases} z_{i+1} = z_i + h[\varphi(x_i, y_i, h) + \delta_{i+1}], & i = 0, 1, \dots, n-1, \\ z_0 = \eta + \delta_0, \end{cases} \quad (3.2)$$

如果存在正常数 C, ε_0, h_0 , 使得对所有 $\varepsilon \in (0, \varepsilon_0]$, $h \in (0, h_0]$, 当 $\max_{0 \leq i \leq n} |\delta_i| \leq \varepsilon$ 时, 有

$$\max_{0 \leq i \leq n} |y_i - z_i| \leq C\varepsilon,$$

则称单步法 (3.1) 稳定.

定理 3.2

在定理 3.1 的条件下, 单步公式 (3.1) 是稳定的.



一般的线性 k 步方法为

$$y_{i+1} = \sum_{j=0}^{k-1} a_j y_{i-j} + h \sum_{j=-1}^{k-1} b_j f(x_{i-j}, y_{i-j}). \quad (4.1)$$

其中 a_{k-1}, b_{k-1} 不同时为零. 当 $b_{-1} = 0$ 时为显式公式; 当 $b_{-1} \neq 0$ 时为隐式公式.

定义 4.1

称

$$R_{i+1} = y(x_{i+1}) - \left[\sum_{j=0}^{k-1} a_j y(x_{i-j}) + h \sum_{j=-1}^{k-1} b_j f(x_{i-j}, y(x_{i-j})) \right]$$

为 k 步公式 (4.1) 在点 x_{i+1} 处的局部截断误差. 当

$$R_{i+1} = O(h^{p+1})$$

时, 称 (4.1) 是 p 阶公式.



定义 4.2

称

$$R_{i+1} = y(x_{i+1}) - \left[\sum_{j=0}^{k-1} a_j y(x_{i-j}) + h \sum_{j=-1}^{k-1} b_j f(x_{i-j}, y(x_{i-j})) \right]$$

为 k 步公式 (4.1) 在点 x_{i+1} 处的局部截断误差. 当

$$R_{i+1} = O(h^{p+1})$$

时, 称 (4.1) 是 p 阶公式.

4.1 基于积分的构造方法 — Adams 公式

将方程 $y'(x) = f(x, y(x))$ 在 $[x_i, x_{i+1}]$ 上积分, 得

$$y(x_{i+1}) = y(x_i) + \int_{x_i}^{x_{i+1}} f(x, y(x)) dx. \quad (4.2)$$

(1) Adams 显式公式

作 $f(x, y(x))$ 以 $x_i, x_{i-1}, \dots, x_{i-r}$ 为插值节点的 r 次 Lagrange 插值多项式 $L_{i,r}(x)$, 有

$$L_{i,r}(x) = \sum_{j=0}^r f(x_{i-j}, y(x_{i-j})) l_{i-j}(x) = \sum_{j=0}^r f(x_{i-j}, y(x_{i-j})) \prod_{\substack{l=0 \\ l \neq j}}^r \frac{x - x_{i-l}}{x_{i-j} - x_{i-l}}.$$

我们有

$$\begin{aligned} f(x, y(x)) &= L_{i,r}(x) + R_{i,r}(x) = L_{i,r}(x) + \frac{1}{(r+1)!} \frac{d^{r+1} f(x, y(x))}{dx^{r+1}} \Big|_{x=\eta_i} \prod_{j=0}^r (x - x_{i-j}) \\ &= L_{i,r}(x) + \frac{1}{(r+1)!} y^{(r+2)}(\eta_i) \prod_{j=0}^r (x - x_{i-j}). \end{aligned}$$

将上式代入 (4.2) 得

$$\begin{aligned}
 y(x_{i+1}) &= y(x_i) + \int_{x_i}^{x_{i+1}} L_{i,r}(x) dx + \int_{x_i}^{x_{i+1}} R_{i,r}(x) dx \\
 &= y(x_i) + \sum_{j=0}^r f(x_{i-j}, y(x_{i-j})) \int_{x_i}^{x_{i+1}} \prod_{\substack{l=0 \\ l \neq j}}^r \frac{x - x_{i-l}}{x_{i-j} - x_{i-l}} dx \\
 &\quad + \frac{1}{(r+1)!} \int_{x_i}^{x_{i+1}} y^{(r+2)}(\eta_i) \prod_{j=0}^r (x - x_{i-j}) dx \\
 &= y(x_i) + h \sum_{j=0}^r f(x_{i-j}, y(x_{i-j})) \int_0^1 \prod_{\substack{l=0 \\ l \neq j}}^r \frac{l+t}{l-j} dt \quad (\text{令 } x = x_i + th) \\
 &\quad + h^{r+2} y^{(r+2)}(\xi_i) \frac{1}{(r+1)!} \int_0^1 \prod_{j=0}^r (j+t) dt. \quad (\text{积分中值定理})
 \end{aligned}$$

其中 $\xi_i \in (x_{i-r}, x_{i+1})$.



记

$$\beta_{rj} = \int_0^1 \prod_{\substack{l=0 \\ l \neq j}}^r \frac{l+t}{l-j} dt, \quad j = 0, 1, \dots, r,$$
$$\alpha_{r+1} = \frac{1}{(r+1)!} \int_0^1 \prod_{j=0}^r (j+t) dt,$$

则

$$y(x_{i+1}) = y(x_i) + h \sum_{j=0}^r \beta_{rj} f(x_{i-j}, y(x_{i-j})) + \alpha_{r+1} h^{r+2} y^{(r+2)}(\xi_i). \quad (4.3)$$

忽略 $\alpha_{r+1} h^{r+2} y^{(r+2)}(\xi_i)$, 并用 y_{i-j} 代替 $y(x_{i-j})$ 得 $(r+1)$ 步 Adams 显式公式:

$$y_{i+1} = y_i + h \sum_{j=0}^r \beta_{rj} f(x_{i-j}, y_{i-j}). \quad (4.4)$$



(4.4) 的局部截断误差是

$$\begin{aligned} R_{i+1} &= y(x_{i+1}) - \left[y(x_i) + h \sum_{j=0}^r \beta_{rj} f(x_{i-j}, y(x_{i-j})) \right] \\ &= \alpha_{r+1} h^{r+2} y^{(r+2)}(\xi_i). \end{aligned}$$

故 (4.4) 是 $(r+1)$ 步、 $(r+1)$ 阶显式的 Adams 公式.

(a) $r=0$, 得 Euler 公式

$$\begin{aligned} y_{i+1} &= y_i + hf(x_i, y_i), \\ R_{i+1} &= \frac{1}{2} h^2 y''(\xi_i), \quad \xi_i \in (x_i, x_{i+1}). \end{aligned}$$

(b) $r=1$, 得

$$\begin{aligned} y_{i+1} &= y_i + \frac{h}{2} [3f(x_i, y_i) - f(x_{i-1}, y_{i-1})], \\ R_{i+1} &= \frac{5}{12} h^3 y^{(3)}(\xi_i), \quad \xi_i \in (x_{i-1}, x_{i+1}). \end{aligned}$$



(c) $r = 2$, 得

$$y_{i+1} = y_i + \frac{h}{12} [23f(x_i, y_i) - 16f(x_{i-1}, y_{i-1}) + 5f(x_{i-2}, y_{i-2})],$$
$$R_{i+1} = \frac{3}{8} h^4 y^{(4)}(\xi_i), \quad \xi_i \in (x_{i-2}, x_{i+1}).$$

(d) $r = 3$, 得

$$y_{i+1} = y_i + \frac{h}{24} [55f(x_i, y_i) - 59f(x_{i-1}, y_{i-1}) + 37f(x_{i-2}, y_{i-2}) - 9f(x_{i-3}, y_{i-3})],$$
$$R_{i+1} = \frac{251}{720} h^5 y^{(5)}(\xi_i), \quad \xi_i \in (x_{i-3}, x_{i+1}).$$

(2) Adams 隐式公式

作 $f(x, y(x))$ 以 $x_{i+1}, x_i, x_{i-1}, \dots, x_{i-r+1}$ 为插值节点的 r 次 Lagrange 插值多项式 $L_{i,r}(x)$, 有

$$L_{i,r}(x) = \sum_{j=-1}^{r-1} f(x_{i-j}, y(x_{i-j})) l_{i-j}(x) = \sum_{j=-1}^{r-1} f(x_{i-j}, y(x_{i-j})) \prod_{\substack{l=-1 \\ l \neq j}}^{r-1} \frac{x - x_{i-l}}{x_{i-j} - x_{i-l}}.$$

我们有

$$\begin{aligned} f(x, y(x)) &= L_{i,r}(x) + R_{i,r}(x) \\ &= L_{i,r}(x) + \frac{1}{(r+1)!} \frac{d^{r+1} f(x, y(x))}{dx^{r+1}} \Big|_{x=\eta_i} \prod_{j=-1}^{r-1} (x - x_{i-j}) \\ &= L_{i,r}(x) + \frac{1}{(r+1)!} y^{(r+2)}(\bar{\eta}_i) \prod_{j=-1}^{r-1} (x - x_{i-j}). \end{aligned}$$

将上式代入 (4.2) 得

$$\begin{aligned}
 y(x_{i+1}) &= y(x_i) + \int_{x_i}^{x_{i+1}} L_{i,r}(x) dx + \int_{x_i}^{x_{i+1}} R_{i,r}(x) dx \\
 &= \sum_{j=-1}^{r-1} f(x_{i-j}, y(x_{i-j})) \int_{x_i}^{x_{i+1}} \prod_{\substack{l=-1 \\ l \neq j}}^{r-1} \frac{x - x_{i-l}}{x_{i-j} - x_{i-l}} dx \\
 &\quad + \frac{1}{(r+1)!} \int_{x_i}^{x_{i+1}} y^{(r+2)}(\bar{\eta}_i) \prod_{j=-1}^{r-1} (x - x_{i-j}) dx \\
 &= y(x_i) + h \sum_{j=-1}^{r-1} f(x_{i-j}, y(x_{i-j})) \int_0^1 \prod_{\substack{l=-1 \\ l \neq j}}^{r-1} \frac{l+t}{l-j} dt \quad (\text{令 } x = x_i + th) \\
 &\quad + h^{r+2} y^{(r+2)}(\bar{\xi}_i) \frac{1}{(r+1)!} \int_0^1 \prod_{j=-1}^{r-1} (j+t) dt. \quad (\text{积分中值定理})
 \end{aligned}$$

其中 $\bar{\xi}_i \in (x_{i-r+1}, x_{i+1})$.

$$\bar{\beta}_{rj} = \int_0^1 \prod_{\substack{l=-1 \\ l \neq j}}^{r-1} \frac{l+t}{l-j} dt, \quad j = 0, 1, \dots, r,$$

$$\bar{\alpha}_{r+1} = \frac{1}{(r+1)!} \int_0^1 \prod_{j=-1}^{r-1} (j+t) dt,$$

则

$$y(x_{i+1}) = y(x_i) + h \sum_{j=-1}^{r-1} \bar{\beta}_{rj} f(x_{i-j}, y(x_{i-j})) + \bar{\alpha}_{r+1} h^{r+2} y^{(r+2)}(\bar{\xi}_i). \quad (4.5)$$

忽略 $\bar{\alpha}_{r+1} h^{r+2} y^{(r+2)}(\bar{\xi}_i)$, 并用 y_{i-j} 代替 $y(x_{i-j})$ 得 r 步 Adams 隐式公式:

$$y_{i+1} = y_i + h \sum_{j=-1}^{r-1} \bar{\beta}_{rj} f(x_{i-j}, y_{i-j}). \quad (4.6)$$



(4.6) 的局部截断误差是

$$\begin{aligned} R_{i+1} &= y(x_{i+1}) - \left[y(x_i) + h \sum_{j=-1}^{r-1} \bar{\beta}_{rj} f(x_{i-j}, y(x_{i-j})) \right] \\ &= \bar{\alpha}_{r+1} h^{r+2} y^{(r+2)}(\bar{\xi}_i). \end{aligned}$$

故 (4.6) 是 r 步、 $(r+1)$ 阶隐式的 Adams 公式.

(a) $r=1$, 得梯形公式

$$\begin{aligned} y_{i+1} &= y_i + \frac{h}{2} [f(x_{i+1}, y_{i+1}) + f(x_i, y_i)], \\ R_{i+1} &= -\frac{1}{12} h^3 y'''(\xi_i), \quad \xi_i \in (x_i, x_{i+1}). \end{aligned}$$



(b) $r = 2$, 得

$$y_{i+1} = y_i + \frac{h}{12} [5f(x_{i+1}, y_{i+1}) + 8f(x_i, y_i) - f(x_{i-1}, y_{i-1})],$$
$$R_{i+1} = -\frac{1}{24} h^4 y^{(4)}(\xi_i), \quad \xi_i \in (x_{i-1}, x_{i+1}).$$

(c) $r = 3$, 得

$$y_{i+1} = y_i + \frac{h}{24} [9f(x_{i+1}, y_{i+1}) + 19f(x_i, y_i) - f(x_{i-1}, y_{i-1}) + f(x_{i-2}, y_{i-2})],$$
$$R_{i+1} = -\frac{19}{720} h^5 y^{(5)}(\xi_i), \quad \xi_i \in (x_{i-2}, x_{i+1}).$$



(3) Admas 预测校正方法

将同阶的显式 Admas 公式和隐式 Admas 公式结合起来, 组成预测校正公式. 如将 2 阶显式 Admas 公式和 2 阶隐式 Asmas 公式结合起来, 得下面的预测校正公式:

$$\begin{cases} y_{i+1}^{(p)} = y_i + \frac{h}{2}[3f(x_i, y_i) - f(x_{i-1}, y_{i-1})], \\ y_{i+1} = y_i + \frac{h}{2}[f(x_{i+1}, y_{i+1}^{(p)}) + f(x_i, y_i)]. \end{cases}$$

又如将 4 阶显式 Admas 公式和 4 阶隐式 Admas 公式组成下面的预测校正公式:

$$\begin{cases} y_{i+1}^{(p)} = y_i + \frac{h}{24}[55f(x_i, y_i) - 59f(x_{i-1}, y_{i-1}) + 37f(x_{i-2}, y_{i-2}) - 9f(x_{i-3}, y_{i-3})], \\ y_{i+1} = y_i + \frac{h}{24}[9f(x_{i+1}, y_{i+1}^{(p)}) + 19f(x_i, y_i) - 5f(x_{i-1}, y_{i-1}) + f(x_{i-2}, y_{i-2})]. \end{cases}$$



4.2 基于 Taylor 展开的待定系数法

要构造下面的线性 k 步方法

$$y_{i+1} = \sum_{j=0}^{k-1} a_j y_{i-j} + h \sum_{j=-1}^{k-1} b_j f(x_{i-j}, y_{i-j}). \quad (4.7)$$

求系数 a_j, b_j , 使公式具有一定的阶数. 局部截断误差为:

$$R_{i+1} = y(x_{i+1}) - \left[\sum_{j=0}^{k-1} a_j y(x_{i-j}) + h \sum_{j=-1}^{k-1} b_j f(x_{i-j}, y(x_{i-j})) \right]$$

利用方程 (0.1) 和 Taylor 展开得

$$\begin{aligned}
 R_{i+1} &= y(x_{i+1}) - \sum_{j=0}^{k-1} a_j y(x_{i-j}) - h \sum_{j=-1}^{k-1} b_j y'(x_{i-j}) \\
 &= \sum_{l=0}^{p+1} \frac{1}{l!} y^{(l)}(x_i) h^l + O(h^{p+2}) - \sum_{j=0}^{k-1} a_j \left[\sum_{l=0}^{p+1} \frac{1}{l!} y^{(l)}(x_i) (-jh)^l + O(h^{p+2}) \right] \\
 &\quad - h \sum_{j=-1}^{k-1} \left[b_j \sum_{l=0}^p \frac{1}{l!} y^{(l+1)}(x_i) (-jh)^l + O(h^{p+1}) \right] \\
 &= \left(1 - \sum_{j=0}^{k-1} a_j \right) y(x_i) + \sum_{l=1}^{p+1} \frac{1}{l!} \left[1 - \sum_{j=0}^{k-1} (-j)^l a_j - l \sum_{j=-1}^{k-1} (-j)^{l-1} b_j \right] h^l y^{(l)}(x_i) + O(h^{p+2}).
 \end{aligned}$$



要使公式 (4.7) 为 p 阶, 则

$$1 - \sum_{j=0}^{k-1} a_j = 0$$
$$1 - \sum_{j=0}^{k-1} (-j)^l a_j - l \sum_{j=-1}^{k-1} (-j)^{l-1} b_j = 0, \quad l = 1, 2, \dots, p.$$

这时局部截断误差为

$$R_{i+1} = \frac{1}{(p+1)!} \left[1 - \sum_{j=0}^{k-1} (-j)^{p+1} a_j - (p+1) \sum_{j=-1}^{k-1} (-j)^p b_j \right] h^{p+1} y^{(p+1)}(x_i) + O(h^{p+2}).$$



例 4.1

给定微分方程初值问题

$$\begin{cases} y'(x) = f(x, y(x)), & a \leq x \leq b, \\ y(a) = \eta, \end{cases}$$

取正整数 n , 并记 $h = (b - a)/n$, $x_i = a + ih$, $0 \leq i \leq n$. 试确定两步公式

$$y_{i+1} = \alpha y_{i-1} + h \left[\beta_0 f(x_{i+1}, y_{i+1}) + \beta_1 f(x_i, y_i) + \beta_2 f(x_{i-1}, y_{i-1}) \right]$$

中的参数 $\alpha, \beta_0, \beta_1, \beta_2$, 使其具有尽可能高的精度, 并指出能达到的阶数.

解 局部截断误差为



$$\begin{aligned}
 R_{i+1} &= y(x_{i+1}) - \alpha y(x_{i-1}) - h[\beta_0 f(x_{i+1}, y(x_{i+1})) + \beta_1 f(x_i, y(x_i)) + \beta_2 f(x_{i-1}, y(x_{i-1}))] \\
 &= y(x_{i+1}) - \alpha y(x_{i-1}) - \beta_0 h y'(x_{i+1}) - \beta_1 h y'(x_i) - \beta_2 h y'(x_{i-1}) \\
 &= y(x_i) + h y'(x_i) + \frac{h^2}{2} y''(x_i) + \frac{h^3}{3!} y'''(x_i) + \frac{h^4}{4!} y^{(4)}(x_i) + \frac{h^5}{5!} y^{(5)}(x_i) + O(h^6) \\
 &\quad - \alpha \left[y(x_i) - h y'(x_i) + \frac{h^2}{2} y''(x_i) - \frac{h^3}{3!} y'''(x_i) + \frac{h^4}{4!} y^{(4)}(x_i) - \frac{h^5}{5!} y^{(5)}(x_i) + O(h^6) \right] \\
 &\quad - \beta_0 h \left[y'(x_i) + h y''(x_i) + \frac{h^2}{2} y'''(x_i) + \frac{h^3}{3!} y^{(4)}(x_i) + \frac{h^4}{4!} y^{(5)}(x_i) + O(h^5) \right] - \beta_1 h y'(x_i) \\
 &\quad - \beta_2 h \left[y'(x_i) - h y''(x_i) + \frac{h^2}{2} y'''(x_i) - \frac{h^3}{3!} y^{(4)}(x_i) + \frac{h^4}{4!} y^{(5)}(x_i) + O(h^5) \right] \\
 &= (1 - \alpha) y(x_i) + (1 + \alpha - \beta_0 - \beta_1 - \beta_2) h y'(x_i) + \left(\frac{1}{2} - \frac{\alpha}{2} - \beta_0 + \beta_2 \right) h^2 y''(x_i) \\
 &\quad + \left(\frac{1}{6} + \frac{\alpha}{6} - \frac{\beta_0}{2} - \frac{\beta_2}{2} \right) h^3 y'''(x_i) + \left(\frac{1}{24} - \frac{\alpha}{24} - \frac{\beta_0}{6} + \frac{\beta_2}{6} \right) h^4 y^{(4)}(x_i) \\
 &\quad + \left(\frac{1}{120} + \frac{\alpha}{120} - \frac{\beta_0}{24} - \frac{\beta_2}{24} \right) h^5 y^{(5)}(x_i) + O(h^6).
 \end{aligned}$$



要使公式精度尽量高, 则

$$1 - \alpha = 0$$

$$1 + \alpha - \beta_0 - \beta_1 - \beta_2 = 0$$

$$\frac{1}{2} - \frac{\alpha}{2} - \beta_0 + \beta_2 = 0$$

$$\frac{1}{6} + \frac{\alpha}{6} - \frac{\beta_0}{2} - \frac{\beta_2}{2} = 0$$

解得 $\alpha = 1, \beta_0 = \frac{1}{3}, \beta_1 = \frac{4}{3}, \beta_2 = \frac{1}{3}$. 此时局部截断误差为

$$R_{i+1} = -\frac{1}{90}h^5 y^{(5)}(x_i) + O(h^6).$$

所以该公式是 4 阶公式.