

# **ZJU Computational Physics: Homework #2**

Due on Monday, December 2, 2024

Github: <https://github.com/NAKONAKO4/ZJU-computational-physics-NAKO>

**NAKO**

## Problem 1

### Derivatives

将 forward formula, central difference formula, Richardson extrapolation 结果绘制在图中进行对比。

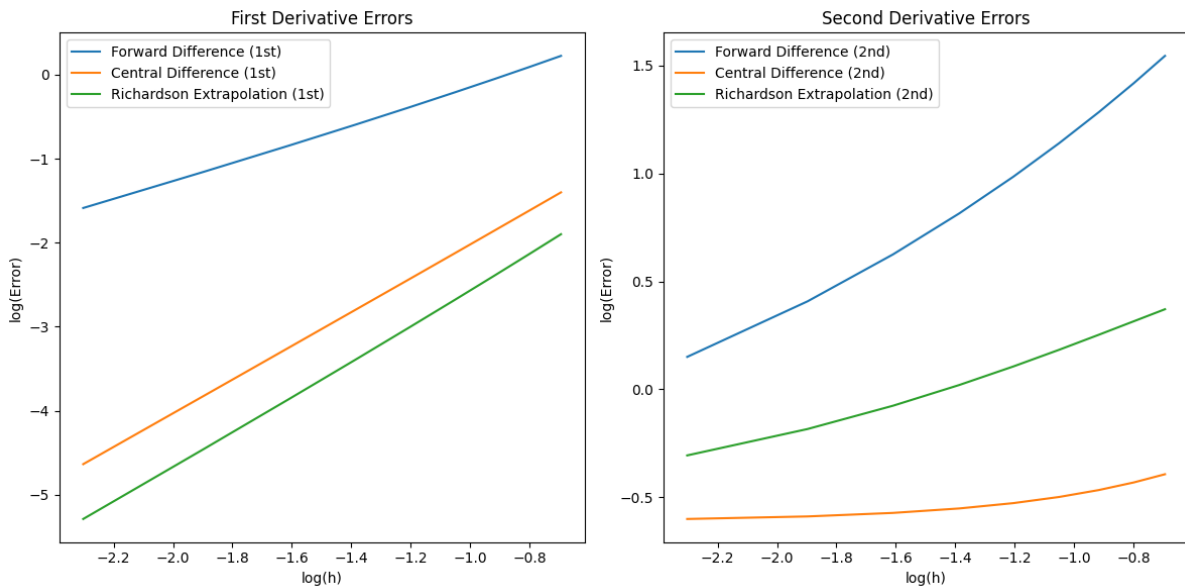
```
1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 def f(x):
5     return x * np.cosh(x)
6
7 def df_exact(x):
8     return np.cosh(x) + x * np.sinh(x)
9
10 def d2f_exact(x):
11     return 2 * np.sinh(x) + x
12
13 def forward_diff(f, x, h):
14     return (f(x + h) - f(x)) / h
15
16 def central_diff(f, x, h):
17     return (f(x + h) - f(x - h)) / (2 * h)
18
19 def forward_diff_second(f, x, h):
20     return (f(x + 2 * h) - 2 * f(x + h) + f(x)) / (h ** 2)
21
22 def central_diff_second(f, x, h):
23     return (f(x + h) - 2 * f(x) + f(x - h)) / (h ** 2)
24
25 def richardson_extrapolation(f_diff, f, x, h, order):
26     D1 = f_diff(f, x, h)
27     D2 = f_diff(f, x, h / 2)
28     return (2 ** order * D2 - D1) / (2 ** order - 1)
29
30 x = 1
31 h_values = np.arange(0.5, 0.05, -0.05)
32 log_h = np.log(h_values)
33
34 log_error_fd1 = []
35 log_error_cd1 = []
36 log_error_fd2 = []
37 log_error_cd2 = []
38 log_error_richardson1 = []
```

```

39 log_error_richardson2 = []
40
41 for h in h_values:
42     # FIRST DERIVATIVE
43     fd1 = forward_diff(f, x, h)
44     cd1 = central_diff(f, x, h)
45     richardson1 = richardson_extrapolation(forward_diff, f, x, h, 1)
46
47     log_error_fd1.append(np.log(np.abs(fd1 - df_exact(x))))
48     log_error_cd1.append(np.log(np.abs(cd1 - df_exact(x))))
49     log_error_richardson1.append(np.log(np.abs(richardson1 - df_exact(x))))
50
51     # SECOND DERIVATIVE
52     fd2 = forward_diff_second(f, x, h)
53     cd2 = central_diff_second(f, x, h)
54     richardson2 = richardson_extrapolation(forward_diff_second, f, x, h, 2)
55
56     log_error_fd2.append(np.log(np.abs(fd2 - d2f_exact(x))))
57     log_error_cd2.append(np.log(np.abs(cd2 - d2f_exact(x))))
58     log_error_richardson2.append(np.log(np.abs(richardson2 - d2f_exact(x))))
59
60 # PLOT LOG ERRORS
61 plt.figure(figsize=(12, 6))
62
63 # FIRST DERIVATIVE
64 plt.subplot(1, 2, 1)
65 plt.plot(log_h, log_error_fd1, label="Forward_Difference_(1st)")
66 plt.plot(log_h, log_error_cd1, label="Central_Difference_(1st)")
67 plt.plot(log_h, log_error_richardson1, label="Richardson_Extrapolation_(1st)")
68 plt.xlabel("log(h)")
69 plt.ylabel("log(Error)")
70 plt.title("First_Derivative_Errors")
71 plt.legend()
72
73 # SECOND DERIVATIVE
74 plt.subplot(1, 2, 2)
75 plt.plot(log_h, log_error_fd2, label="Forward_Difference_(2nd)")
76 plt.plot(log_h, log_error_cd2, label="Central_Difference_(2nd)")
77 plt.plot(log_h, log_error_richardson2, label="Richardson_Extrapolation_(2nd)")
78 plt.xlabel("log(h)")
79 plt.ylabel("log(Error)")
80 plt.title("Second_Derivative_Errors")
81 plt.legend()
82
83 plt.tight_layout()
84 plt.show()

```

运行结果为



b. 参见/1/b.py，图像中可见仍然存在一定的与实际值的误差。

运行结果为

Two-Point Derivatives: [1.0020006678319593, 4.004016292524781, 4.041794454678893, 27.673419111806652, -166.31140908884845]  
 Three-Point Derivatives: [1.0000006666652794, 4.000009333426924, 3.999918007924208, 27.999956520030622, -164.0181046536071]  
 Five-Point Derivatives: [1.000000000054594, 4.000004666780299, 3.99994533561987, 27.999918300603, -164.0088620469271]

```

1 import numpy as np
2
3 def f(x):
4     return np.exp(x) / (np.sin(x)**3 + np.cos(x)**3)
5
6 def two_point(f, x, h, n):
7     if n == 1:
8         return (f(x + h) - f(x)) / h
9     else:
10        return (two_point(f, x + h, h, n - 1) - two_point(f, x, h, n - 1)) / h
11
12 def three_point(f, x, h, n):
13     if n == 1:
14         return (f(x + h) - f(x - h)) / (2 * h)
15     else:
16         return (three_point(f, x + h, h, n - 1) - three_point(f, x - h, h, n - 1)) / (2 * h)
17
18 def five_point(f, x, h, n):
19     if n == 1:

```

---

```

20         return (-f(x + 2 * h) + 8 * f(x + h) - 8 * f(x - h) + f(x - 2 * h)) / (12 * h)
21     else:
22         return (five_point(f, x + h, h, n - 1) - five_point(f, x - h, h, n - 1)) / (2 * h)
23
24 x = 0
25 h = 0.001 # STEP SIZE. CHANGE HERE TO REDUCE THE ERROR.
26 derivatives = 5
27
28 results_two_point = [two_point(f, x, h, n) for n in range(1, derivatives + 1)]
29 results_three_point = [three_point(f, x, h, n) for n in range(1, derivatives + 1)]
30 results_five_point = [five_point(f, x, h, n) for n in range(1, derivatives + 1)]
31
32 print("Two-Point_Derivatives:", results_two_point)
33 print("Three-Point_Derivatives:", results_three_point)
34 print("Five-Point_Derivatives:", results_five_point)

```

---

## Problem 2

### Integration

---

```

1  import numpy as np
2
3  def f1(x):
4      return np.log(x)
5
6  def f2(x):
7      return np.exp(-x**2)
8
9  def f3(x):
10     return 1 / (1 + x**2)
11
12 def trapezoid_n(a, b, error_tolerance, second_derivative_max):
13     return int(np.ceil(np.sqrt(((b - a)**3 * second_derivative_max) / (12 * error_tolerance)
14         )))
15
16 def simpson_n(a, b, error_tolerance, fourth_derivative_max):
17     return int(np.ceil((((b - a)**5 * fourth_derivative_max) / (180 * error_tolerance))
18         *(1/4)))
19
20 f1_second_derivative_max = 1
21 f1_fourth_derivative_max = 1
22
23 f2_second_derivative_max = 2
24 f2_fourth_derivative_max = 12
25
26 f3_second_derivative_max = 4

```

```

25 f3_fourth_derivative_max = 24
26
27 epsilon1 = 1e-8
28 epsilon2 = 1e-10
29 epsilon3 = 1e-12
30
31 n1_trap = trapezoid_n(1, 3, epsilon1, f1_second_derivative_max)
32 n1_simp = simpson_n(1, 3, epsilon1, f1_fourth_derivative_max)
33
34 n2_trap = trapezoid_n(-1, 1, epsilon2, f2_second_derivative_max)
35 n2_simp = simpson_n(-1, 1, epsilon2, f2_fourth_derivative_max)
36
37 n3_trap = trapezoid_n(1/2, 5/2, epsilon3, f3_second_derivative_max)
38 n3_simp = simpson_n(1/2, 5/2, epsilon3, f3_fourth_derivative_max)
39
40 print("I1(log(x)): Trapezoid n=", n1_trap, ", Simpson n=", n1_simp)
41 print("I2(exp(-x^2)): Trapezoid n=", n2_trap, ", Simpson n=", n2_simp)
42 print("I3(1/(1+x^2)): Trapezoid n=", n3_trap, ", Simpson n=", n3_simp)

```

运行结果为:

```

I1 (log(x)): Trapezoid n = 8165 , Simpson n = 65
I2 (exp(-x^2)): Trapezoid n = 115471 , Simpson n = 383
I3 (1/(1+x^2)): Trapezoid n = 1632994 , Simpson n = 1438

```

整理如下

	Trapezoid n	Simpson n
$I_1(\log(x))$	8165	65
$I_2(\exp(-x^2))$	115471	383
$I_3(1/(1+x^2))$	1632994	1438

## Problem 3

### Hilbert Matrix

通过 python numpy 库的 `linalg.eigvals()` 函数可以直接将矩阵对角化并计算出矩阵的特征值。本题目使用了 numpy 库的 `linalg.eigvals()` 函数来对角化矩阵并计算特征值。

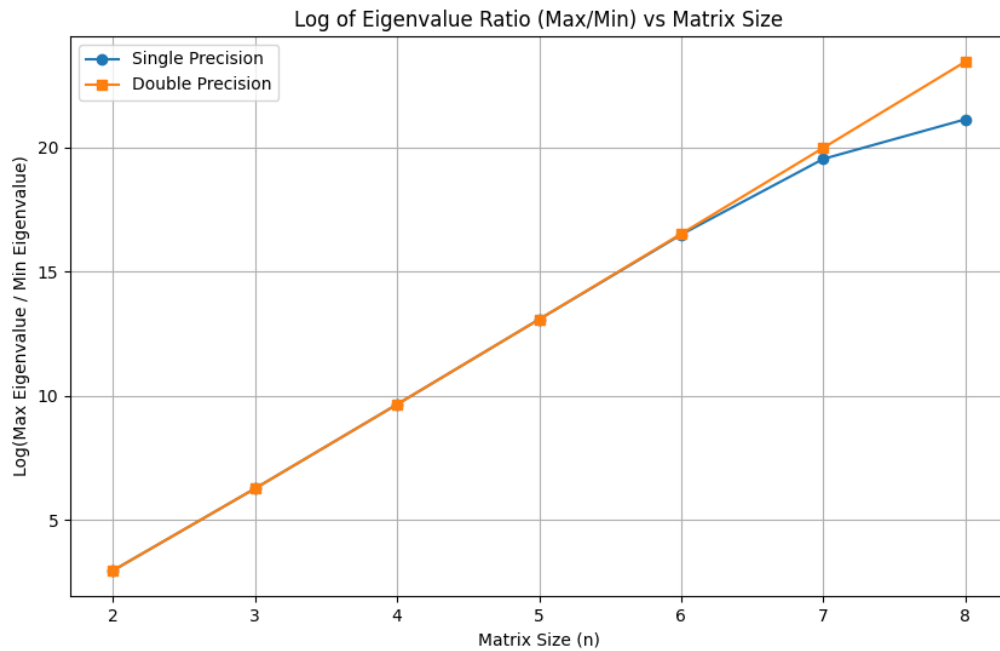
```

1 import numpy as np

```

```
2 import matplotlib.pyplot as plt
3
4
5 def hilbert_matrix(n):
6     return np.array([[1 / (i + j + 1) for j in range(n)] for i in range(n)])
7
8
9 def eigenvalue_ratio_log(matrix):
10     eigenvalues = np.linalg.eigvals(matrix)
11     max_eigenvalue = np.max(np.abs(eigenvalues))
12     min_eigenvalue = np.min(np.abs(eigenvalues))
13     return np.log(max_eigenvalue / min_eigenvalue)
14
15
16 n_values = range(2, 9)
17
18 ratios_single = []
19 ratios_double = []
20
21 for n in n_values:
22     H = hilbert_matrix(n)
23
24     # SINGLE PRECISION
25     H_single = H.astype(np.float32)
26     ratios_single.append(eigenvalue_ratio_log(H_single))
27
28     # DOUBLE PRECISION
29     H_double = H.astype(np.float64)
30     ratios_double.append(eigenvalue_ratio_log(H_double))
31
32 plt.figure(figsize=(10, 6))
33 plt.plot(n_values, ratios_single, marker='o', label="Single Precision")
34 plt.plot(n_values, ratios_double, marker='s', label="Double Precision")
35 plt.title("Log of Eigenvalue Ratio (Max/Min) vs Matrix Size")
36 plt.xlabel("Matrix Size (n)")
37 plt.ylabel("Log(Max Eigenvalue / Min Eigenvalue)")
38 plt.legend()
39 plt.grid()
40 plt.show()
```

---



## Problem 4

### Coupled Oscillators

a. 设置耦合系数为 1, 每个振子的质量为 1, 在  $T=10$  的模拟时长进行计算。首先通过欧拉方法来求解数值解, 并与通过模态展开得到的解析解结果的  $u_j(t)$  进行对比。可以得到结果为

```
Oscillator 1: Maximum Difference = 0.023230, Relative Error = 0.039907
Oscillator 2: Maximum Difference = 0.034412, Relative Error = 0.050140
Oscillator 3: Maximum Difference = 0.028043, Relative Error = 0.038147
Oscillator 4: Maximum Difference = 0.019648, Relative Error = 0.028608
Oscillator 5: Maximum Difference = 0.019422, Relative Error = 0.028863
Oscillator 6: Maximum Difference = 0.021836, Relative Error = 0.032791
Oscillator 7: Maximum Difference = 0.023721, Relative Error = 0.035859
Oscillator 8: Maximum Difference = 0.015188, Relative Error = 0.023069
Oscillator 9: Maximum Difference = 0.014331, Relative Error = 0.021847
Oscillator 10: Maximum Difference = 0.015219, Relative Error = 0.023298
Oscillator 11: Maximum Difference = 0.013294, Relative Error = 0.022193
Oscillator 12: Maximum Difference = 0.004273, Relative Error = 0.013044
```



可以看到，欧拉方法得到的差值结果较大，相对误差较大。

于是我又尝试了用 Runge-Kutta 4th 方法去进行上述计算，得到结果如下

```
Oscillator 1: Maximum Difference = 0.0000000197, Relative Error = 0.0000000339
Oscillator 2: Maximum Difference = 0.0000000250, Relative Error = 0.0000000365
Oscillator 3: Maximum Difference = 0.0000000261, Relative Error = 0.0000000298
Oscillator 4: Maximum Difference = 0.0000000212, Relative Error = 0.0000000287
Oscillator 5: Maximum Difference = 0.0000000124, Relative Error = 0.0000000166
Oscillator 6: Maximum Difference = 0.0000000237, Relative Error = 0.0000000313
Oscillator 7: Maximum Difference = 0.0000000286, Relative Error = 0.0000000353
Oscillator 8: Maximum Difference = 0.0000000350, Relative Error = 0.0000000479
Oscillator 9: Maximum Difference = 0.0000000272, Relative Error = 0.0000000347
Oscillator 10: Maximum Difference = 0.0000000280, Relative Error = 0.0000000297
Oscillator 11: Maximum Difference = 0.0000000220, Relative Error = 0.0000000291
Oscillator 12: Maximum Difference = 0.0000000201, Relative Error = 0.0000000394
```

可以看到 Runge-Kutta 4th 方法得到的精度明显高于欧拉方法。

欧拉方法

```
1 import numpy as np
2
3 N = 12
4 K = 1.0
5 m = 1.0
6 dt = 0.01
7 T = 10
8
9 frequencies = np.array([2 * np.sqrt(K / m) * np.sin((k * np.pi) / (2 * (N + 1))) for k in
    range(1, N + 1)])
10 modes = np.array([[np.sin((k * j * np.pi) / (N + 1)) for j in range(1, N + 1)] for k in
    range(1, N + 1)])
11 A_k = np.array([
12     (2 / (N + 1)) * np.sum(
13         [np.sin((k * j * np.pi) / (N + 1)) * (1 if j == 3 else 0) for j in range(1, N + 1)]
14     ) / frequencies[k - 1]
15     for k in range(1, N + 1)
16 ])
17
18 def analytical_solution(t, j):
19     return np.sum([
20         A_k[k] * modes[k, j - 1] * np.sin(frequencies[k] * t)
21         for k in range(N)
```

```

22     ])
23
24 def euler_method(dt, T, N, K, m):
25     time_steps = int(T / dt)
26     u = np.zeros((time_steps, N))
27     v = np.zeros((time_steps, N))
28     u[0, :] = 0
29     v[0, 2] = 1
30
31     for t in range(1, time_steps):
32         for j in range(N):
33             left = u[t - 1, j - 1] if j > 0 else 0
34             right = u[t - 1, j + 1] if j < N - 1 else 0
35             a_j = K / m * (left - 2 * u[t - 1, j] + right)
36             v[t, j] = v[t - 1, j] + dt * a_j
37             u[t, j] = u[t - 1, j] + dt * v[t - 1, j]
38
39     return u, v
40
41 time_points = np.arange(0, T, dt)
42 u_num, v_num = euler_method(dt, T, N, K, m)
43
44 u_analytic = np.zeros_like(u_num)
45 for t_idx, t in enumerate(time_points):
46     for j in range(1, N + 1):
47         u_analytic[t_idx, j - 1] = analytical_solution(t, j)
48
49 max_differences_per_oscillator = np.max(np.abs(u_analytic - u_num), axis=0)
50 relative_errors_per_oscillator = max_differences_per_oscillator / np.max(np.abs(u_analytic),
51                                     axis=0)
52
53 for j, (max_diff, rel_error) in enumerate(zip(max_differences_per_oscillator,
54                                             relative_errors_per_oscillator), start=1):
55     print(f"Oscillator_{j}: Maximum_Difference={max_diff:.6f}, Relative_Error={rel_error:.6f}")

```

### Runge-Kutta 4th 方法

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 N = 12
5 K = 1.0
6 m = 1.0
7 dt = 0.01
8 T = 100

```

```

9
10 frequencies = np.array([2 * np.sqrt(K / m) * np.sin((k * np.pi) / (2 * (N + 1))) for k in
    range(1, N + 1)])
11 modes = np.array([[np.sin((k * j * np.pi) / (N + 1)) for j in range(1, N + 1)] for k in
    range(1, N + 1)])
12 A_k = np.array([
13     (2 / (N + 1)) * np.sum(
14         [np.sin((k * j * np.pi) / (N + 1)) * (1 if j == 3 else 0) for j in range(1, N + 1)]
15     ) / frequencies[k - 1]
16     for k in range(1, N + 1)
17 ])
18
19 def analytical_solution(t, j):
20     return np.sum([
21         A_k[k] * modes[k, j - 1] * np.sin(frequencies[k] * t)
22         for k in range(N)
23     ])
24
25 def rk4_method(dt, T, N, K, m):
26     time_steps = int(T / dt)
27     u = np.zeros((time_steps, N))
28     v = np.zeros((time_steps, N))
29     u[0, :] = 0
30     v[0, 2] = 1
31
32     def acceleration(u):
33         acc = np.zeros(N)
34         for j in range(N):
35             left = u[j - 1] if j > 0 else 0
36             right = u[j + 1] if j < N - 1 else 0
37             acc[j] = K / m * (left - 2 * u[j] + right)
38         return acc
39
40     for t in range(1, time_steps):
41         k1_u = v[t - 1]
42         k1_v = acceleration(u[t - 1])
43
44         k2_u = v[t - 1] + 0.5 * dt * k1_v
45         k2_v = acceleration(u[t - 1] + 0.5 * dt * k1_u)
46
47         k3_u = v[t - 1] + 0.5 * dt * k2_v
48         k3_v = acceleration(u[t - 1] + 0.5 * dt * k2_u)
49
50         k4_u = v[t - 1] + dt * k3_v
51         k4_v = acceleration(u[t - 1] + dt * k3_u)
52
53         u[t] = u[t - 1] + dt / 6 * (k1_u + 2 * k2_u + 2 * k3_u + k4_u)

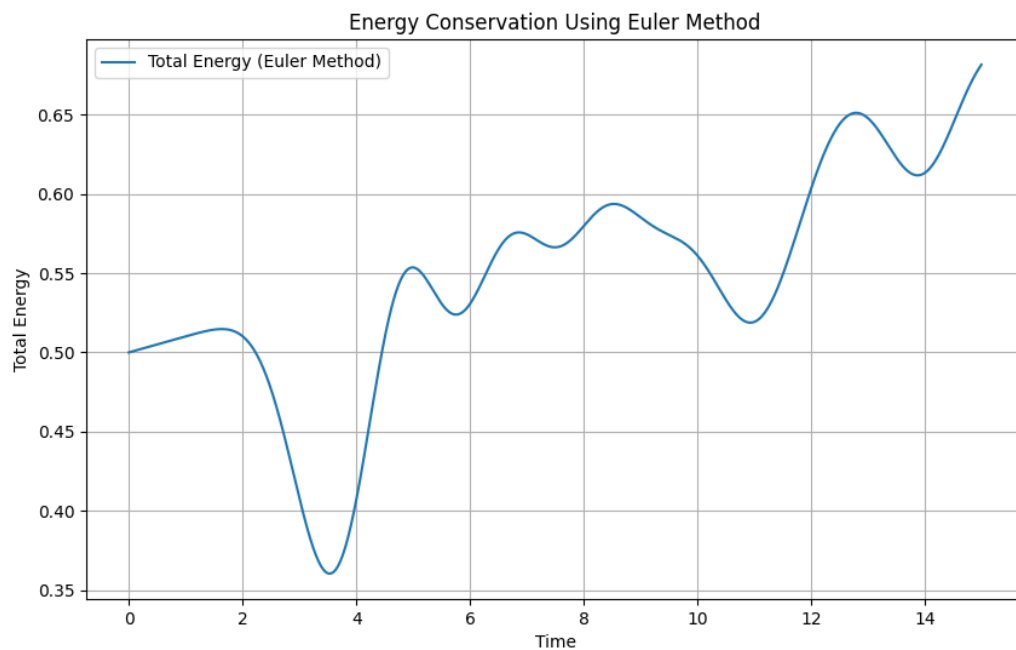
```

```

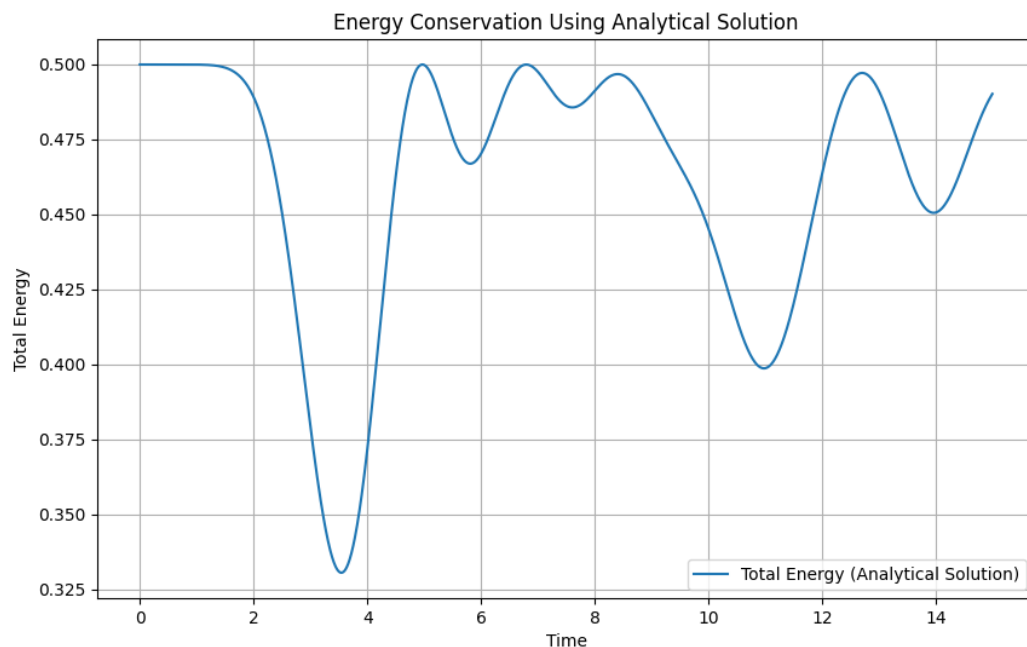
54     v[t] = v[t - 1] + dt / 6 * (k1_v + 2 * k2_v + 2 * k3_v + k4_v)
55
56     return u, v
57
58 time_points = np.arange(0, T, dt)
59 u_num, v_num = rk4_method(dt, T, N, K, m)
60
61 u_analytic = np.zeros_like(u_num)
62 for t_idx, t in enumerate(time_points):
63     for j in range(1, N + 1):
64         u_analytic[t_idx, j - 1] = analytical_solution(t, j)
65
66 difference = np.abs(u_analytic - u_num)
67
68 max_differences_per_oscillator = np.max(np.abs(u_analytic - u_num), axis=0)
69 relative_errors_per_oscillator = max_differences_per_oscillator / np.max(np.abs(u_analytic),
    axis=0)
70
71 for j, (max_diff, rel_error) in enumerate(zip(max_differences_per_oscillator,
    relative_errors_per_oscillator), start=1):
72     print(f"Oscillator_{j}: Maximum_Difference={max_diff:.10f}, Relative_Error={
        rel_error:.10f}")

```

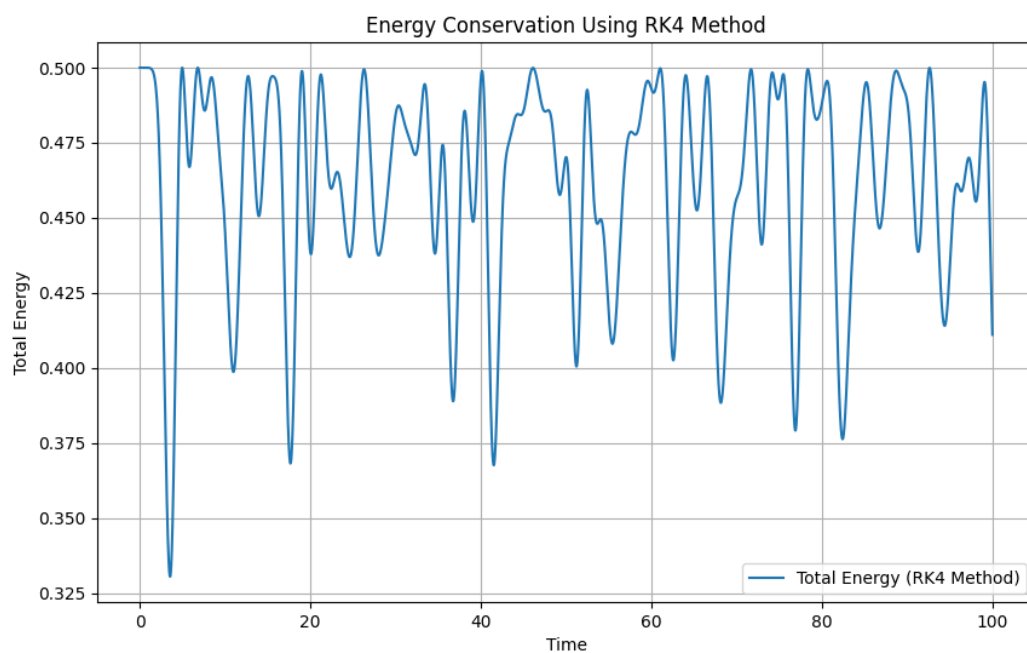
b. 采用欧拉方法计算，得到结果如下



但事实上与解析解能量进行对比可以看到，欧拉方法与解析解能量并不吻合。



同时也可以看到，在更长的时间上进行计算，解析解的能量守恒并不是很好，在初始能量 0.5 下面波动，但是均值还是在 0.475 附近，存在一些比较大的波动到达 0.375 附近。



---

```

1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 N = 12
5 K = 1.0
6 m = 1.0
7 dt = 0.01
8 T = 15
9
10 frequencies = np.array([2 * np.sqrt(K / m) * np.sin((k * np.pi) / (2 * (N + 1))) for k in
    range(1, N + 1)])
11 modes = np.array([[np.sin((k * j * np.pi) / (N + 1)) for j in range(1, N + 1)] for k in
    range(1, N + 1)])
12 A_k = np.array([
13     (2 / (N + 1)) * np.sum(
14         [np.sin((k * j * np.pi) / (N + 1)) * (1 if j == 3 else 0) for j in range(1, N + 1)]
15     ) / frequencies[k - 1]
16     for k in range(1, N + 1)
17 ])
18
19 def analytical_solution(t, j):
20     return np.sum([
21         A_k[k] * modes[k, j - 1] * np.sin(frequencies[k] * t)
22         for k in range(N)
23     ])
24
25
26 def euler_method(dt, T, N, K, m):
27     time_steps = int(T / dt)
28     u = np.zeros((time_steps, N))
29     v = np.zeros((time_steps, N))
30     u[0, :] = 0
31     v[0, 2] = 1
32
33     for t in range(1, time_steps):
34         for j in range(N):
35             left = u[t - 1, j - 1] if j > 0 else 0
36             right = u[t - 1, j + 1] if j < N - 1 else 0
37             a_j = K / m * (left - 2 * u[t - 1, j] + right)
38             v[t, j] = v[t - 1, j] + dt * a_j
39             u[t, j] = u[t - 1, j] + dt * v[t - 1, j]
40
41     return u, v
42
43 time_points = np.arange(0, T, dt)
44 u_num, v_num = euler_method(dt, T, N, K, m)

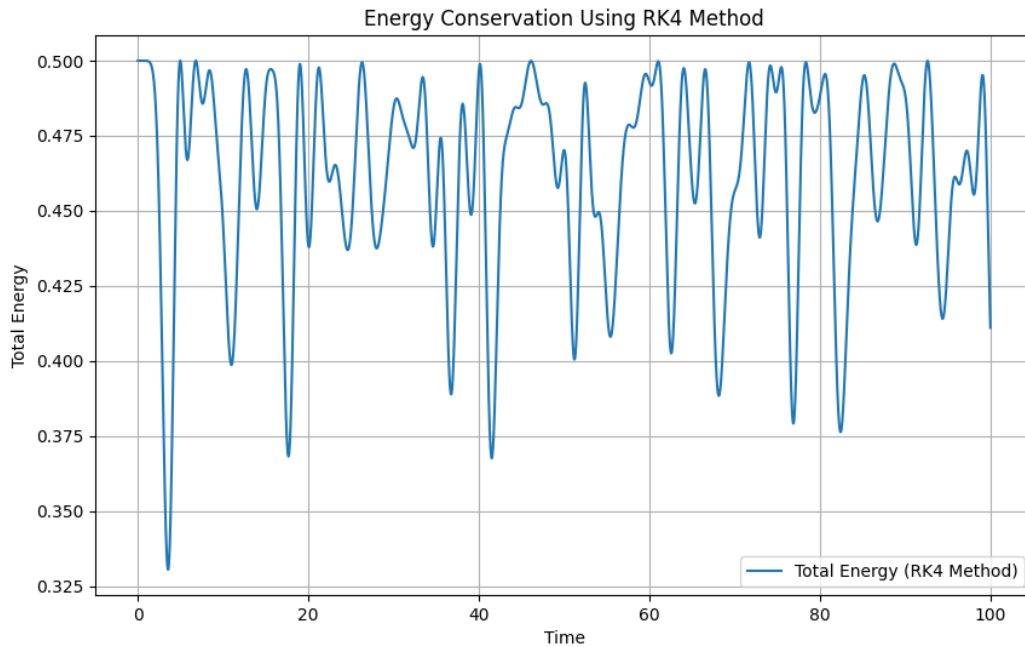
```

```

45
46 u_analytic = np.zeros_like(u_num)
47 for t_idx, t in enumerate(time_points):
48     for j in range(1, N + 1):
49         u_analytic[t_idx, j - 1] = analytical_solution(t, j)
50 def compute_total_energy(u, v, K, m):
51     kinetic_energy = 0.5 * m * np.sum(v**2, axis=1)
52     potential_energy = 0.5 * K * np.sum((np.diff(u, axis=1))**2, axis=1)
53     return kinetic_energy + potential_energy
54
55 energy_values = compute_total_energy(u_num, v_num, K, m)
56
57 plt.figure(figsize=(10, 6))
58 plt.plot(time_points, energy_values, label="Total_Energy_(Euler_Method)")
59 plt.title("Energy_Conservation_Using_Euler_Method")
60 plt.xlabel("Time")
61 plt.ylabel("Total_Energy")
62 plt.legend()
63 plt.grid()
64 plt.show()
65
66 def compute_energy_analytic(u_analytic, K, m, time_points):
67     v_analytic = np.zeros_like(u_analytic)
68     for t_idx, t in enumerate(time_points):
69         for j in range(1, N + 1):
70             v_analytic[t_idx, j - 1] = np.sum([
71                 A_k[k] * modes[k, j - 1] * frequencies[k] * np.cos(frequencies[k] * t)
72                 for k in range(N)
73             ])
74     kinetic_energy = 0.5 * m * np.sum(v_analytic**2, axis=1)
75     potential_energy = 0.5 * K * np.sum((np.diff(u_analytic, axis=1))**2, axis=1)
76     return kinetic_energy + potential_energy
77
78 analytic_energy_values = compute_energy_analytic(u_analytic, K, m, time_points)
79
80 import matplotlib.pyplot as plt
81
82 plt.figure(figsize=(10, 6))
83 plt.plot(time_points, analytic_energy_values, label="Total_Energy_(Analytical_Solution)")
84 plt.title("Energy_Conservation_Using_Analytical_Solution")
85 plt.xlabel("Time")
86 plt.ylabel("Total_Energy")
87 plt.legend()
88 plt.grid()
89 plt.show()

```

c. 结果如下，可以看到跟解析解十分吻合，同样也是没有很好的能量守恒，存在一些较大的波动，整体均值在接近初始能量 0.5 附近。



```

1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 N = 12
5 K = 1.0
6 m = 1.0
7 dt = 0.01
8 T = 100
9
10 frequencies = np.array([2 * np.sqrt(K / m) * np.sin((k * np.pi) / (2 * (N + 1))) for k in
11     range(1, N + 1)])
12 modes = np.array([[np.sin((k * j * np.pi) / (N + 1)) for j in range(1, N + 1)] for k in
13     range(1, N + 1)])
14 A_k = np.array([
15     (2 / (N + 1)) * np.sum(
16         [np.sin((k * j * np.pi) / (N + 1)) * (1 if j == 3 else 0) for j in range(1, N + 1)]
17     ) / frequencies[k - 1]
18     for k in range(1, N + 1)
19 ])
20
21 def analytical_solution(t, j):
22     return np.sum([
23         A_k[k] * modes[k, j - 1] * np.sin(frequencies[k] * t)

```



```

22         for k in range(N)
23     ])
24
25 def rk4_method(dt, T, N, K, m):
26     time_steps = int(T / dt)
27     u = np.zeros((time_steps, N))
28     v = np.zeros((time_steps, N))
29     u[0, :] = 0
30     v[0, 2] = 1
31
32     def acceleration(u):
33         acc = np.zeros(N)
34         for j in range(N):
35             left = u[j - 1] if j > 0 else 0
36             right = u[j + 1] if j < N - 1 else 0
37             acc[j] = K / m * (left - 2 * u[j] + right)
38         return acc
39
40     for t in range(1, time_steps):
41         k1_u = v[t - 1]
42         k1_v = acceleration(u[t - 1])
43
44         k2_u = v[t - 1] + 0.5 * dt * k1_v
45         k2_v = acceleration(u[t - 1] + 0.5 * dt * k1_u)
46
47         k3_u = v[t - 1] + 0.5 * dt * k2_v
48         k3_v = acceleration(u[t - 1] + 0.5 * dt * k2_u)
49
50         k4_u = v[t - 1] + dt * k3_v
51         k4_v = acceleration(u[t - 1] + dt * k3_u)
52
53         u[t] = u[t - 1] + dt / 6 * (k1_u + 2 * k2_u + 2 * k3_u + k4_u)
54         v[t] = v[t - 1] + dt / 6 * (k1_v + 2 * k2_v + 2 * k3_v + k4_v)
55
56     return u, v
57
58 time_points = np.arange(0, T, dt)
59 u_num, v_num = rk4_method(dt, T, N, K, m)
60
61 u_analytic = np.zeros_like(u_num)
62 for t_idx, t in enumerate(time_points):
63     for j in range(1, N + 1):
64         u_analytic[t_idx, j - 1] = analytical_solution(t, j)
65
66 difference = np.abs(u_analytic - u_num)
67
68 plt.figure(figsize=(12, 8))

```

```

69 for j in range(1, N + 1):
70     plt.plot(time_points, difference[:, j - 1], label=f'Oscillator_{j}')
71
72 plt.title("Difference_Between_Analytical_and_RK4_Numerical_Solutions")
73 plt.xlabel("Time")
74 plt.ylabel("Difference_in_Displacement")
75 plt.legend(loc='upper_right', fontsize='small')
76 plt.grid()
77 plt.show()
78
79
80
81 v_analytic = np.zeros_like(v_num)
82
83 for t_idx, t in enumerate(time_points):
84     for j in range(1, N + 1):
85         v_analytic[t_idx, j - 1] = np.sum([
86             A_k[k] * modes[k, j - 1] * frequencies[k] * np.cos(frequencies[k] * t)
87             for k in range(N)
88         ])
89
90 def compute_energy(u, v, K, m):
91     kinetic_energy = 0.5 * m * np.sum(v**2, axis=1)
92     potential_energy = 0.5 * K * np.sum((np.diff(u, axis=1))**2, axis=1)
93     return kinetic_energy + potential_energy
94
95 rk4_energy_values = compute_energy(u_num, v_num, K, m)
96
97 import matplotlib.pyplot as plt
98
99 plt.figure(figsize=(10, 6))
100 plt.plot(time_points, rk4_energy_values, label="Total_Energy_(RK4_Method)")
101 plt.title("Energy_Conservation_Using_RK4_Method")
102 plt.xlabel("Time")
103 plt.ylabel("Total_Energy")
104 plt.legend()
105 plt.grid()
106 plt.show()
107
108 def compute_energy_analytic(u_analytic, K, m, time_points):
109     v_analytic = np.zeros_like(u_analytic)
110     for t_idx, t in enumerate(time_points):
111         for j in range(1, N + 1):
112             v_analytic[t_idx, j - 1] = np.sum([
113                 A_k[k] * modes[k, j - 1] * frequencies[k] * np.cos(frequencies[k] * t)
114                 for k in range(N)
115             ])

```

```
116     kinetic_energy = 0.5 * m * np.sum(v_analytic**2, axis=1)
117     potential_energy = 0.5 * K * np.sum((np.diff(u_analytic, axis=1))**2, axis=1)
118     return kinetic_energy + potential_energy
119
120 analytic_energy_values = compute_energy_analytic(u_analytic, K, m, time_points)
121
122 import matplotlib.pyplot as plt
123
124 plt.figure(figsize=(10, 6))
125 plt.plot(time_points, analytic_energy_values, label="Total_Energy_(Analytical_Solution)")
126 plt.title("Energy_Conconservation_Using_Analytical_Solution")
127 plt.xlabel("Time")
128 plt.ylabel("Total_Energy")
129 plt.legend()
130 plt.grid()
131 plt.show()
```

---