Advanced methods for ODEs - Lab exercises

1. FFT and IFFT in MATLAB:

Use the Fast Fourier Transform to compute compute the k-th derivative of an appropriate function.

In MATLAB the interface for this function could look like y=fft_diff_k(N,I,f,k), with the following input variables:

- N: number of grid points
- *I*: interval for the grid
- f: the function to differentiate
- k: order of differentiation

Test you method and verify the results with an appropriate function, e.g.

$$f(x) = \cos\left(\frac{x}{16}\right) \left(1 + \sin\left(\frac{x}{16}\right)\right)$$

on $[0, 32\pi]$.

Possible solution:

```
% Exercise 1
1
   function y=Exercise1(N,I,f,k)
2
   %Gridpoints
3
   x=linspace(I(1),I(2),N+1)'; x=x(1:N);
4
   %Interval length & scaling factor
\mathbf{5}
   l=I(2)-I(1); sf=sqrt(1)/N;
6
   %shifted and scaled versions of fft/ifft
7
   myfft=@(x)fftshift(fft(x))*sf;
8
   myifft=@(x) ifft(ifftshift(x))/sf;
9
10
   u=f(x);
   %fft transformed of u_hat
11
12
   u_hat=myfft(u);
   %wave numbers
13
   lambda=(-N/2:N/2-1) '*2*pi/l;
14
   %compute k-derivative in frequency space
15
   y_hat = (1i*lambda).^k.*u_hat;
16
17
   %transform back
18
   y=(myifft(y_hat));
```

```
Listing 1: Exercise 1
```

```
% Exercise 1
1
  N=128;
2
   c=32;
3
   x=linspace(0,c*pi,N+1);x=x(1:N)';
4
   f=Q(x)\cos(x/16).*(1+\sin(x/16));
\mathbf{5}
   fs=Q(x)-1/16*sin(x/16).*(1+sin(x/16))+1/16*cos(x/16).^2;
6
   u=f(x):
7
   subplot(2,2,1), plot(x,u); title('function');
8
   subplot(2,2,2), plot(x,fs(x)); title('first derivative');
9
10
   %fft transformed of u_hat
   v=Exercise1(N,[0,32*pi],f,1);
11
   subplot(2,2,4), plot(x,v); title('first derivative -fft');
12
   subplot(2,2,3), semilogy(x,abs(v-fs(x))); title('absolute error');
13
   norm(v-fs(x))
14
```

Listing 2: Example use of Exercise 1

2. Computing φ -functions via the matrix exponential

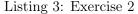
Implement a function that computes

$$y = \sum_{\ell=0}^{p} \tau^{\ell} \varphi_{\ell}(\tau A) v_{\ell}$$

See the excerpt of [Al-Mohy and Higham 2011, Ch. 2] in the appendix. In particular formula (2.11) should be implemented. Be aware of the order of the vectors v_{ℓ} .

Possible solution:

```
function y=phi(tau,A,v)
1
  p = size(v, 2) - 1;
3
   J=spdiags(ones(p,1),1,p,p);
4
\mathbf{5}
   W = v(:, end: -1:2);
  nw=norm(W,inf);
6
   eta = 2^-min(ceil(log2(max(nw,realmin))));
7
   B = [A, eta*W; zeros(p, size(A, 2)), J];
8
   ep=flipud(eye(p,1));
9
   v0=[v(:,1); ep/eta];
10
   y=full([speye(size(A)), sparse(length(A), p)]*expm(tau*B)*v0);
11
```



For the following PDEs in one space dimension we use periodic boundary conditions in $[0, 2\pi]$ and as initial value one can use $u_0(x) = e^{-100(x-3)^2}$. Discretise the space with N (even) grid points in the same fashion as in the first example. As a first iteration N = 128 is a fine enough grid. As final time use T = 1.

- 3. Linear PDEs
 - (a) Solve the advection (transport) equation

$$\partial_t u = c_1 \partial_x u$$

exactly by the formula

$$u(t) = u_0(x + tc_1)$$

and with the help of the previous exercises by a FFT approach. For the experiments one can use e.g. $c_1 = \pi$ to move the initial condition for a half turn.

(b) Use the same FFT approach to solve the heat equation

$$\partial_t u = c_2 \partial_x^2 u.$$

For the experiment one can use $c_2 = 0.4$ as a first test.

(c) Solve the advection-diffusion equation

$$\partial_t u = c_1 \partial_x u + c_2 \partial_x^2 u$$

with FFT. Use c_1, c_2 as before.

Possible solution:

```
%Configuration
1
\mathbf{2}
   N=256; I=[0,2*pi];
   x=linspace(I(1),I(2),N+1)'; x=x(1:N);
3
   %Interval length & scaling factor
4
   l=I(2)-I(1); sf=sqrt(1)/N;
5
   %shifted and scaled versions of fft/ifft
6
7
   myfft=@(x)fftshift(fft(x))*sf;
   myifft=@(x)real(ifft(ifftshift(x)))/sf;
8
9
   %Parameters
10
   c=[0.9,0.1]; T=10;
   u0=@(x) exp(-100*(x-3).^2);
11
12
   %timestep for animation
13
   h = (I(2) - I(1)) / N / 4;
15
   %%% Animated compuation %%%%%%%%%
   %%% advection exact
16
   %disp('advection exact');
17
   %for t=0:h:T
18
         v=u0(mod(x+c(1)*t,2*pi));
19
   %
   %
         plot(x,v), ylim([0,1]); pause(0.01);
20
21
   %end
22
   %%% advection fft
23
   disp('advection fft');
24
   %pause
   v=u0(x):
25
26
   lambda=(-N/2:N/2-1) '*2*pi/1;
   L=exp(c(1)*h*1i*lambda);%+c(2)*h*(1i*k).^2);
27
28
   for t=0:h:T
29
        v=myifft(L.*myfft(v));
        plot(x,v); ylim([-0.1,1]); pause(0.01);
30
31
   end
32
   %%% diffusion fft
   disp('diffusion fft');
33
   %pause
34
   v=u0(x);
35
   L=exp(c(2)*h*(1i*lambda).^2);
36
   for t=0:h:T
37
        v=myifft(L.*myfft(v));
38
        plot(x,v); ylim([0,1]); pause(0.01);
39
40
   end
   %%% advection-diffusion fft
41
42
   disp('advection-diffusion fft');
43
   pause
44
   v=u0(x);
45
   L=\exp(c(1)*h*1i*lambda+c(2)*h*(1i*lambda).^2);
   for t=0:h:T
46
        v=myifft(L.*myfft(v));
47
48
        plot(x,v); ylim([0,1]); pause(0.01);
   end
49
```

Listing 4: Exercise 3

4. LIE AND STRANG SPLITTING

Implement a method for the Lie splitting

$$u_1 = \mathrm{e}^{\tau B} \mathrm{e}^{\tau A} u_0$$

and Strang splitting

$$u_1 = \mathrm{e}^{\frac{1}{2}\tau A} \mathrm{e}^{\tau B} \mathrm{e}^{\frac{1}{2}\tau A} u_0.$$

Assume that no dense output is required and optimise Strang splitting accordingly. Use these implementations and test them for the *phenomenon* splitting of the advectiondiffusion equation

$$\partial_t u = \underbrace{c_1 \partial_x}_{=:B} u + \underbrace{c_2 \partial_x^2}_{=:A} u.$$

As a second example test your implementation for the advection-diffusion-reaction equation

$$\partial_t u = \underbrace{\left(c_1 \partial_x + c_2 \partial_x^2\right)}_{=:A} u + \underbrace{g(u)}_{=:B}$$

where for the nonlinearity can be with the exact flow or by a Runge–Kutta method like (ode45). Use g(u) = b the constant function and g(u) = (1 - u)u for your experiments.

Possible solution:

```
1 function y=lie(h,A,B,u0,T)
2 step=@(v)B(h,A(h,v));
3 y=u0;
4 for t=h:h:T
5 y=step(y);
6 end
```

Listing 5: Lie

```
1 function y=strang_naive(h,A,B,u0,T)
2 step=@(v)A(h/2,B(h,A(h/2,v)));
3 y=u0;
4 for t=h:h:T
5 y=step(y);
6 end
```

Listing 6: Strang naive

```
1 function y=strang(h,A,B,u0,T)
2 step=@(v)B(h,A(h,v));
3 y=B(h,A(h/2,u0));
4 for t=h:h:(T-h)
5 y=step(y);
6 end
7 y=A(h/2,y);
```

Listing 7: Strang

5. EXPONENTIAL EULER

Implement an exponential Euler method

$$u_1 = \mathrm{e}^{\tau A} u_0 + \tau \varphi_1(\tau A) g(u_0)$$

with the help of Exercise 2 where we implemented a function to compute linear combinations of φ -functions. As a test example use

$$\partial_t u = \underbrace{\left(c_1 \partial_x + c_1 \partial_x^2\right)}_{=:A} u + g(u)$$

for g as in the previous example i.e. g(u) = b and g(u) = (1 - u)u. Possible solution:

```
1 function y=expEuler(h,A,g,u0,T)
2 y=u0;
3 for t=h:h:T
4 y=phi(h,A,[y,g(y)]);
5 end
```

Listing 8: Exponential Euler

6. EXPONENTIAL RUNGE-KUTTA

Implement the exponential Runge–Kutta method of order two given by the Butcher tableau

$$\begin{array}{c|c} 0 \\ 1 \\ \hline \varphi_1 \\ \hline \varphi_1 - \varphi_2 \\ \varphi_2 \end{array}$$

or a single step as

$$u_1 = e^{\tau A} u_0 + \tau \varphi_1(\tau A) g(u_0) + \tau^2 \varphi_2(\tau A) \left(\frac{g(U_1) - g(u_0)}{\tau}\right)$$
$$U_1 = e^{\tau A} u_0 + \tau \varphi_1(\tau A) g(u_0)$$

As a test equation use the same equations as in the previous exercise.

Possible solution:

```
function y=exprk2(h,A,g,u0,T)
1
\mathbf{2}
   y=u0;
3
    for t=h:h:T
       y=step(h,A,g,y);
4
\mathbf{5}
    end
         function y=step(h,A,g,u0)
7
             gu=g(u0);
8
             U1=phi(h,A,[u0,gu]);
9
10
             y=phi(h,A,[u0,gu,(g(U1)-gu)/h]);
^{11}
         end
    end
12
```

Listing 9: Exponential Runge–Kutta of order 2

Possible solution:

```
%Configuration
1
   N=128; I=[0,2*pi];
2
   x=linspace(I(1),I(2),N+1)'; x=x(1:N);
3
   %Interval length & scaling factor
4
   l=I(2)-I(1); sf=sqrt(1)/N;
5
   \% {\rm shifted} and scaled versions of fft/ifft
6
   myfft=@(x)fftshift(fft(x))*sf;
7
8
   myifft=@(x)real(ifft(ifftshift(x)))/sf;
   lambda=(-N/2:N/2-1) '*2*pi/1;
9
   %Parameters
10
   c=[0.9,0.1,0.1]; T=1;
11
   u0=@(x)exp(-100*(x-3).^2);
12
   %timestep for animation
13
14
   h=T/round(T/((I(2)-I(1))/N/4));
   v=u0(x);
16
   g=@(v)c(3)*(v.*(1-v));
17
   g_ei=@(v)myfft(c(3)*(myifft(v).*(1-myifft(v))));
18
   A_op=@(h,v)myifft(exp(c(1)*h*1i*lambda+c(2)*h*(1i*lambda).^2).*myfft(v));
19
20 A=spdiags((c(2)*(1i*lambda).^2+c(1)*(1i*lambda)),0,N,N);
```

```
options = odeset('RelTol',1e-13,'AbsTol',1e-15);
21
   B_op=@(h,v)deval(ode45(@(t,x)g(x),[0 h],v,options),h);
22
   odefun=@(t,y)myifft((c(2)*(1i*lambda).^2+c(1)*(1i*lambda)).*myfft(y))+g(y);
23
   yode=deval(ode45(odefun,[0,T/2,T],v,options),T);
24
   H=2.^(-1*(0:1:10));
25
   e=zeros(length(H),4);
26
   for i=1:length(H);
27
^{28}
        h=H(i);
29
        e(i,1)=norm(yode-lie(h,A_op,B_op,v,T),inf);
        e(i,2)=norm(yode-strang(h,A_op,B_op,v,T),inf);
30
        e(i,3)=norm(yode-myifft(expEuler(h,A,g_ei,myfft(v),T)),inf);
31
        e(i,4)=norm(yode-myifft(exprk2(h,A,g_ei,myfft(v),T)),inf);
32
   end
33
   loglog(H,e)
34
   legend('lie','strang','expEuler','exprk2')
35
```

Listing 10: Order plot for Lie, Strang, expEuler, exprk2

7. Solve the Kuramoto-Sivashinsky equation - Exercise

On $[0, 32\pi]$ solve the Kuramoto-Sivashinsky equation

$$\partial_t u = -\partial_x^4 u - \partial_x^2 u - u \partial_x u$$

for the initial value

$$u_0 = \cos\left(\frac{x}{16}\right) \left(1 + \sin\left(\frac{x}{16}\right)\right)$$

with a splitting and exponential integrator approach on the interval $[0, 32\pi]$ for final time T = 150 and an appropriate step size τ .

For the splitting select appropriate splitting operators with the Strang splitting and use the exponential Runge–Kutta method as exponential integrator.

HINT: The nonlinearity can be solved exactly by the method of characteristicss.

References

Al-Mohy, A.H., Higham, N.J., 2011. Computing the action of the matrix exponential, with an application to exponential integrators. SIAM J. Sci. Comput. 33 (2), 488–511.

A Appendix

2. Exponential integrators: avoiding the φ functions. Exponential integrators are a class of time integration methods for solving initial value problems written in the form

(2.1)
$$u'(t) = Au(t) + g(t, u(t)), \quad u(t_0) = u_0, \quad t \ge t_0,$$

where $u(t) \in \mathbb{C}^n$, $A \in \mathbb{C}^{n \times n}$, and g is a nonlinear function. Spatial semidiscretization of partial differential equations (PDEs) leads to systems in this form. The matrix A usually represents the Jacobian of a certain function or an approximation of it, and it is usually large and sparse. The solution of (2.1) satisfies the nonlinear integral equation

(2.2)
$$u(t) = e^{(t-t_0)A}u_0 + \int_{t_0}^t e^{(t-\tau)A}g(\tau, u(\tau)) d\tau.$$

By expanding g in a Taylor series about t_0 , the solution can be written as [17, Lem. 5.1]

(2.3)
$$u(t) = e^{(t-t_0)A}u_0 + \sum_{k=1}^{\infty} \varphi_k \big((t-t_0)A \big) (t-t_0)^k u_k,$$

where

$$u_k = \frac{d^{k-1}}{dt^{k-1}}g(t, u(t)) \mid_{t=t_0}, \quad \varphi_k(z) = \frac{1}{(k-1)!} \int_0^1 e^{(1-\theta)z} \theta^{k-1} \, d\theta, \quad k \ge 1.$$

By suitably truncating the series in (2.3), we obtain the approximation

(2.4)
$$u(t) \approx \widehat{u}(t) = e^{(t-t_0)A}u_0 + \sum_{k=1}^p \varphi_k \big((t-t_0)A \big) (t-t_0)^k u_k$$

The functions $\varphi_{\ell}(z)$ satisfy the recurrence relation

$$\varphi_{\ell}(z) = z\varphi_{\ell+1}(z) + \frac{1}{\ell!}, \quad \varphi_0(z) = e^z,$$

and have the Taylor expansion

(2.5)
$$\varphi_{\ell}(z) = \sum_{k=0}^{\infty} \frac{z^k}{(k+\ell)!}.$$

A wide class of exponential integrator methods is obtained by employing suitable approximations to the vectors u_k in (2.4), and further methods can be obtained by the use of different approximations to g in (2.2). See Hochbruck and Ostermann [15] for a survey of the state of the art in exponential integrators.

We will show that the right-hand side of (2.4) can be represented in terms of the single exponential of an $(n + p) \times (n + p)$ matrix, with no need to explicitly evaluate φ functions. The following theorem is our key result. In fact we will only need the special case of the theorem with $\ell = 0$.

THEOREM 2.1. Let $A \in \mathbb{C}^{n \times n}$, $W = [w_1, w_2, \dots, w_p] \in \mathbb{C}^{n \times p}$, $\tau \in \mathbb{C}$, and

(2.6)
$$\widetilde{A} = \begin{bmatrix} A & W \\ 0 & J \end{bmatrix} \in \mathbb{C}^{(n+p)\times(n+p)}, \quad J = \begin{bmatrix} 0 & I_{p-1} \\ 0 & 0 \end{bmatrix} \in \mathbb{C}^{p\times p}.$$

Then for $X = \varphi_{\ell}(\tau \widetilde{A})$ with $\ell \ge 0$ we have

(2.7)
$$X(1:n,n+j) = \sum_{k=1}^{j} \tau^{k} \varphi_{\ell+k}(\tau A) w_{j-k+1}, \quad j=1:p.$$

Proof. It is easy to show that, for $k \ge 0$,

(2.8)
$$\widetilde{A}^k = \begin{bmatrix} A^k & M_k \\ 0 & J^k \end{bmatrix},$$

where $M_k = A^{k-1}W + M_{k-1}J$ and $M_1 = W$, $M_0 = 0$. For $1 \le j \le p$ we have $WJ(:, j) = w_{j-1}$ and JJ(:, j) = J(:, j-1), where we define both right-hand sides to

be zero when j = 1. Thus

$$M_k(:,j) = A^{k-1}w_j + (A^{k-2}W + M_{k-2}J)J(:,j)$$

= $A^{k-1}w_j + A^{k-2}w_{j-1} + M_{k-2}J(:,j-1)$
= $\dots = \sum_{i=1}^{\min(k,j)} A^{k-i}w_{j-i+1}.$

We will write $M_k(:, j) = \sum_{i=1}^{j} A^{k-i} w_{j-i+1}$ on the understanding that when k < j we set to zero the terms in the summation where i > k (i.e., those terms with a negative power of A). From (2.5) and (2.8) we see that the (1,2) block of $X = \varphi_{\ell}(\tau \widetilde{A})$ is

$$X(1:n, n+1:n+p) = \sum_{k=1}^{\infty} \frac{\tau^k M_k}{(k+\ell)!}.$$

Therefore, the (n+j)th column of X is given by

$$\begin{aligned} X(1:n,n+j) &= \sum_{k=1}^{\infty} \frac{\tau^k M_k(:,j)}{(k+\ell)!} = \sum_{k=1}^{\infty} \frac{1}{(k+\ell)!} \left(\sum_{i=1}^{j} \tau^i (\tau A)^{k-i} w_{j-i+1} \right) \\ &= \sum_{i=1}^{j} \tau^i \left(\sum_{k=1}^{\infty} \frac{(\tau A)^{k-i}}{(k+\ell)!} \right) w_{j-i+1} \\ &= \sum_{i=1}^{j} \tau^i \left(\sum_{k=0}^{\infty} \frac{(\tau A)^k}{(\ell+k+i)!} \right) w_{j-i+1} = \sum_{i=1}^{j} \tau^i \varphi_{\ell+i}(\tau A) w_{j-i+1}. \end{aligned}$$

With $\tau = 1$, j = p, and $\ell = 0$, Theorem 2.1 shows that, for arbitrary vectors w_k , the sum of matrix-vector products $\sum_{k=1}^{p} \varphi_k(A) w_{j-k+1}$ can be obtained from the last column of the exponential of a matrix of dimension n + p. A special case of the theorem is worth noting. On taking $\ell = 0$ and $W = [c \ 0] \in \mathbb{C}^{n \times p}$, where $c \in \mathbb{C}^n$, we obtain $X(1:n, n+j) = \tau^j \varphi_j(\tau A)c$, which is a relation useful for Krylov methods that was derived by Sidje [22, Thm. 1]. This in turn generalizes the expression

$$\exp\left(\begin{bmatrix} A & c\\ 0 & 0 \end{bmatrix}\right) = \begin{bmatrix} e^A & \varphi_1(A)c\\ 0 & I \end{bmatrix}$$

obtained by Saad [21, Prop. 1].

We now use the theorem to obtain an expression for (2.4) involving only the matrix exponential. Let $W(:, p - k + 1) = u_k$, k = 1: p, form the matrix \tilde{A} in (2.6), and set $\ell = 0$ and $\tau = t - t_0$. Then

(2.9)
$$X = \varphi_0 \left((t - t_0) \widetilde{A} \right) = e^{(t - t_0) \widetilde{A}} = \begin{bmatrix} e^{(t - t_0) A} & X_{12} \\ 0 & e^{(t - t_0) J} \end{bmatrix},$$

where the columns of X_{12} are given by (2.7), and, in particular, the last column of X_{12} is

$$X(1:n,n+p) = \sum_{k=1}^{p} \varphi_k ((t-t_0)A)(t-t_0)^k u_k.$$

Hence, by (2.4) and (2.9),

(2.10)

$$\widehat{u}(t) = e^{(t-t_0)A}u_0 + \sum_{k=1}^p \varphi_k \big((t-t_0)A \big) (t-t_0)^k u_k \\
= e^{(t-t_0)A}u_0 + X(1:n,n+p) \\
= \begin{bmatrix} I_n & 0 \end{bmatrix} e^{(t-t_0)\widetilde{A}} \begin{bmatrix} u_0 \\ e_p \end{bmatrix}.$$

Thus we are approximating the nonlinear system (2.1) by a subspace of a slightly larger linear system

$$y'(t) = \widetilde{A}y(t), \quad y(t_0) = \begin{bmatrix} u_0 \\ e_p \end{bmatrix}.$$

To evaluate (2.10) we need to compute the action of the matrix exponential on a vector. We focus on this problem in the rest of the paper.

An important practical matter concerns the scaling of \tilde{A} . If we replace W by ηW we see from (2.7) that the only effect on $X = e^{\tilde{A}}$ is to replace X(1:n, n+1:n+p) by $\eta X(1:n, n+1:n+p)$. This linear relationship can also be seen using properties of the Fréchet derivative [11, Thm. 4.12]. For methods employing a scaling and squaring strategy a large ||W|| can cause overscaling, resulting in numerical instability. To avoid overscaling a suitable normalization of W is necessary. In the 1-norm we have

$$||A||_1 \le ||\widetilde{A}||_1 \le \max(||A||_1, \eta ||W||_1 + 1)$$

since $||J||_1 = 1$. We choose $\eta = 2^{-\lceil \log_2(||W||_1)\rceil}$, which is defined as a power of 2 to avoid the introduction of rounding errors. The variant of the expression (2.10) that we should evaluate is

(2.11)
$$\widehat{u}(t) = \begin{bmatrix} I_n & 0 \end{bmatrix} \exp\left((t-t_0) \begin{bmatrix} A & \eta W \\ 0 & J \end{bmatrix}\right) \begin{bmatrix} u_0 \\ \eta^{-1}e_p \end{bmatrix}$$

Experiment 8 in Section 6 illustrates the importance of normalizing W.