MTH 410/510 II: Final Project, due by noon on 03/21/2019

Estimation of distributed source parameters for a nonlinear dynamical system

The goal of this project is to apply constrained optimization techniques for estimating spacedistributed source parameters (forcing term) in a nonlinear dynamical system. Issues related with parameter estimation (identifiability) are also illustrated.

SETUP. Consider the initial-boundary value problem (IBVP) for the function u(x,t),

$$\begin{cases}
 u_t(x,t) - u_{xx}(x,t) + u^3(x,t) = \alpha(x), & \forall 0 < x < 1, \ \forall t > 0 \\
 u(0,t) = 0, \ u(1,t) = 0, \ \forall t > 0 \\
 u(x,0) = u_0(x), \ 0 \le x \le 1
\end{cases}$$
(1)

Physically, the IBVP problem (1) models a diffusion process $u_t - u_{xx}$ with a nonlinear reaction term u^3 , and a space-dependent parameter (source/forcing term), $\alpha(x)$. The initial state $u_0(x)$ at time $t_0 = 0$ is assumed to be known. In this assignment we want to find an optimal **space-distributed** parameter α^* such that the solution to (1) is as close as possible to a given function (desired outcome/goal, measurement) $\bar{u}(x)$, as explained below.

A discrete version to the IBVP (1) is obtained by considering a uniform partition of the spatial domain [0, 1] with nodes $\{x_i : i = 0 : n+1\}$ at an increment h = 1/(n+1),

$$0 = x_0 < x_1 < \ldots < x_n < x_{n+1} = 1, \quad x_i = i * h, \text{ for } i = 0 : n+1$$

and a time increment (step) $\Delta t = k$ to advance the state in time from $t_0 = 0$,

$$t_i = t_{i-1} + k$$
, for $j = 1, 2, \dots$

The second-order derivative in space is approximated as

$$u_{xx}(x_i, t_j) \approx \frac{u(x_{i+1}, t_j) - 2u(x_i, t_j) + u(x_{i-1}, t_j)}{h^2}, \quad i = 1 : n, \ j \ge 0$$
 (2)

and the first-order time derivative is approximated as

$$u_t(x_i, t_j) \approx \frac{u(x_i, t_{j+1}) - u(x_i, t_j)}{k}, \quad i = 1 : n, \ j \ge 0$$
 (3)

The discrete version to the IBVP (1) for $u_{i,j} \approx u(x_i, t_j), i = 1: n, j = 0, 1, ...$ is obtained as

$$\begin{cases}
\frac{u_{i,j+1} - u_{i,j}}{k} - \frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{h^2} + u_{i,j}^3 = \alpha_i, & i = 1:n, \ j = 0, 1, \dots \\
u_{0,j} = 0, \quad u_{n+1,j} = 0, \ j = 1, 2, \dots \text{ (boundary condition)} \\
u_{i,0} = u_0(x_i), \quad i = 0:n+1, \text{ (initial condition)}
\end{cases} \tag{4}$$

where $\alpha_i = \alpha(x_i), i = 1:n$.

THE DISCRETE DYNAMICAL SYSTEM. In a compact format, the system of equations (4) to advance the state from time t_{i-1} to time t_i is written

$$\mathbf{u}_j = \mathbf{A}\mathbf{u}_{j-1} - k\mathbf{F}(\mathbf{u}_{j-1}) + k\boldsymbol{\alpha}, \quad j = 1, 2, \dots$$
 (5)

where the notation is as follows:

$$\mathbf{A} \in \mathbb{R}^{n \times n}, \ \mathbf{A} = \begin{pmatrix} 1 - 2s & s & 0 \\ s & \ddots & \ddots & \\ & \ddots & \ddots & s \\ 0 & & s & 1 - 2s \end{pmatrix}, \ s \stackrel{def}{=} \frac{k}{h^2}$$

$$\mathbf{u}_{j} \in \mathbb{R}^{n}, \ \mathbf{u}_{j} = \begin{bmatrix} u_{1,j} \\ u_{2,j} \\ \vdots \\ u_{n,j} \end{bmatrix}, j = 0, 1, \dots; \ \boldsymbol{\alpha} \in \mathbb{R}^{n}, \ \boldsymbol{\alpha} = \begin{bmatrix} \alpha_{1} \\ \alpha_{2} \\ \vdots \\ \alpha_{n} \end{bmatrix}, \ \mathbf{F} : \mathbb{R}^{n} \to \mathbb{R}^{n}, \ \mathbf{F}(\mathbf{u}) = \begin{bmatrix} u_{1}^{3} \\ u_{2}^{3} \\ \vdots \\ u_{n}^{3} \end{bmatrix}$$

THE OPTIMIZATION PROBLEM. With a specified initial condition \mathbf{u}_0 , the discrete system (5) defines the time evolution of the state vector \mathbf{u} as a function of the parameter vector $\boldsymbol{\alpha}$. Optimal parameter values $\boldsymbol{\alpha}^* \in \mathbb{R}^n$ are obtained by minimizing the distance between the model predicted state \mathbf{u}_m at time t_m and a data set $\widetilde{\mathbf{u}}_m$ (measurements or goal values) specified at time t_m . The optimality criteria is formulated as a constrained optimization problem,

$$\min_{[\boldsymbol{\alpha}, \mathbf{u}_1, \mathbf{u}_2, \dots \mathbf{u}_m]} \frac{1}{2} \|\mathbf{u}_m - \widetilde{\mathbf{u}}_m\|^2$$
 (6)

subject to the constraints

$$\mathbf{u}_{j} = \mathbf{A}\mathbf{u}_{j-1} - k\mathbf{F}(\mathbf{u}_{j-1}) + k\boldsymbol{\alpha}, \quad j = 1:m$$
(7)

Notice that in this formulation the number of parameters is $(n + m \times n)$. The Lagrangian function is $\mathcal{L}: \mathbb{R}^n \times \mathbb{R}^{n \times m} \times \mathbb{R}^{n \times m}$,

$$\mathscr{L}(\boldsymbol{\alpha}, \mathbf{u}, \boldsymbol{\lambda}) = \frac{1}{2} \|\mathbf{u}_m - \widetilde{\mathbf{u}}_m\|^2 - \sum_{j=1}^m \boldsymbol{\lambda}_j^{\mathrm{T}} \cdot [\mathbf{u}_j - \mathbf{A}\mathbf{u}_{j-1} + k\mathbf{F}(\mathbf{u}_{j-1}) - k\boldsymbol{\alpha}]$$
(8)

where $\mathbf{u} = [\mathbf{u}_1, \mathbf{u}_2, \dots \mathbf{u}_m]$ is the time-series of the model state, $\lambda_j \in \mathbb{R}^n$ denotes the vector of Lagrange variables at time $t_j, j = 1 : m$ and $\lambda = [\lambda_1, \lambda_2, \dots \lambda_m] \in \mathbb{R}^{n \times m}$.

First-order optimality conditions are

$$\nabla_{\mathbf{u}_m} \mathcal{L} = \mathbf{u}_m - \widetilde{\mathbf{u}}_m - \boldsymbol{\lambda}_m = \mathbf{0}$$
 (9)

$$\nabla_{\mathbf{u}_j} \mathcal{L} = -\boldsymbol{\lambda}_j + \left[\mathbf{A} - k\mathbf{F}'(\mathbf{u}_j)\right]^{\mathrm{T}} \boldsymbol{\lambda}_{j+1} = \mathbf{0}, \quad j = m-1:-1:1$$
(10)

$$\nabla_{\alpha} \mathcal{L} = k \sum_{j=1}^{m} \lambda_{j} = \mathbf{0}$$
 (11)

where $\mathbf{F}'(\mathbf{u})$ denotes the Jacobian matrix of $\mathbf{F}(\mathbf{u})$, here a diagonal matrix, $\mathbf{F}'(\mathbf{u}) = diag(3\mathbf{u}.^2)$.

Alternatively, we may formulate an unconstrained optimization problem, by using the model equations (5) to express \mathbf{u}_m in terms of the input parameters $\boldsymbol{\alpha}$. The reduced problem is

$$\alpha^* = \arg\min_{\alpha} f(\alpha), \quad f(\alpha) \stackrel{def}{=} \frac{1}{2} \|\mathbf{u}_m(\alpha) - \widetilde{\mathbf{u}}_m\|^2$$
 (12)

The gradient of the cost functional (12), $\nabla_{\alpha} f(\alpha)$, may be evaluated as follows:

Backward Integration (Adjoint Model):

$$\lambda_m \stackrel{def}{=} \mathbf{u}_m - \widetilde{\mathbf{u}}_m \tag{13}$$

for
$$j = m - 1 : -1 : 1$$
 (14)

$$\boldsymbol{\lambda}_{j} \stackrel{def}{=} \left[\mathbf{A} - k \mathbf{F}'(\mathbf{u}_{j}) \right]^{\mathrm{T}} \boldsymbol{\lambda}_{j+1}$$
 (15)

end
$$(16)$$

$$\nabla_{\alpha} f(\alpha) = k \sum_{j=1}^{m} \lambda_j$$
 (17)

PROJECT DATA. The data to implement this project is specified as follows.

- initial condition: $u_0(x) = \sin(2\pi x)$.
- dimension of the state vector: n = 49; this gives an x-increment of h = 1/(n+1) = 0.02
- time step: $k = 0.5h^2$ (thus s = 0.5) and number of time steps: m = 100
- $\widetilde{\mathbf{u}}_m$ data at time t_m : given in data file prdata1.m
- $\tilde{\mathbf{u}}_{2m}$ validation data at time t_{2m} (see below why needed): given in data file prdata2.m

PROJECT TASKS

Task 1 (10 points). Implement a function $\mathbf{u} = ibvpmodel(n, m, h, \boldsymbol{\alpha}, \mathbf{u}_0)$ that takes as input a parameter vector $\boldsymbol{\alpha}$, an initial condition \mathbf{u}_0 , the state dimension n, the number of time steps m, and the grid parameter h and returns the time-distributed state \mathbf{u} obtained from equations (7) with $k = 0.5h^2$.

Task 2 (80 points). Use a method of your choice to find the optimal parameters $\alpha^* \in \mathbb{R}^n$ and the associated time-series of states \mathbf{u}^* by solving (6-7) or the reduced problem (12). Provide:

- The plot (spatial distribution) of the optimal parameter values α^* .
- The plot of the model state \mathbf{u}_m^{\star} fit to data $\widetilde{\mathbf{u}}_m$ at time t_m .
- The value of cost function $f(\alpha^*)$.
- Validation procedure: The plot of the model state \mathbf{u}_{2m}^{\star} fit to data $\widetilde{\mathbf{u}}_{2m}$ at time t_{2m} .

Task 3 (10 points). Repeat the experiments at Task 2 but using the initial condition $u_0(x) = \sin(\pi x)$. Comment on your results.

Attach a listing/hardcopy of the codes used to implement the functions at Tasks 1 and 2.