

Geometric Integration and Lie group methods,  
THREAD  
Network-wide training event 6

January 30, 2021

**SECOND ASSIGNMENT.** You have learned about discrete gradient methods for preserving invariants in ODEs. In this assignment you shall apply the same technique for a PDE. But it is then necessary to give some background information first. For a PDE, the first integral is usually an integral over the whole spatial domain of a function that depends not only on the solution  $u(x, t)$ , but also on its spatial derivatives,  $u_x, u_{xx}$  etc, so for instance with one space dimension we could have something like

$$H[u] = \int_{\mathbb{R}} G(u(x, t), u_x(x, t), u_{xx}(x, t), \dots) dx$$

What was in the ODE case the gradient of  $H$  is now replaced by the *variational derivative*  $\frac{\delta H}{\delta u}$  which is defined through the relation

$$\left. \frac{\partial}{\partial \varepsilon} \right|_{\varepsilon=0} H[u + \varepsilon v] = \left\langle \frac{\delta H}{\delta u}, v \right\rangle_{L^2}$$

Looking at the example

$$H[u] = \int_{\mathbb{R}} \left( \frac{1}{2} u_x^2 - u^3 \right) dx \tag{1}$$

you may verify, using integration by parts and the fact that  $u$  must vanish at infinity

$$\frac{\delta H}{\delta u} = -u_{xx} - 3u^2 \tag{2}$$

The skew-symmetric matrix you saw in the ODE case has now been replaced by an operator which is skew-symmetric with respect to the  $L^2$  inner product. For instance, one could choose

$$\mathcal{S} = \frac{\partial}{\partial x} \tag{3}$$

which is skew-symmetric with respect to the  $L^2$  inner product. So we have arrived at the PDE itself, which is now written in the form

$$u_t = \mathcal{S} \frac{\delta H}{\delta u}. \tag{4}$$

Now, using the examples suggested above with invariant (1), and skew-symmetric operator (3), we would get, using (2) and (4), the KdV equation

$$u_t = -6uu_x - u_{xxx} \quad (5)$$

We shall be using the KdV equation as our case in this assignment. To make it simpler to implement, we also assume that we have periodic boundary conditions, i.e.

$$u(-L, t) = u(L, t), \quad \text{for all } t$$

and an initial condition of the form

$$u(x, 0) = \frac{c}{2} \operatorname{sech}^2\left(\frac{\sqrt{c}}{2}x\right)$$

Then the exact solution is  $u(x, t) = \frac{c}{2} \operatorname{sech}^2\left(\frac{\sqrt{c}}{2}(x - ct)\right)$

**Exercise.** Let  $\langle \cdot, \cdot \rangle_{\mathbb{R}^K}$  be the euclidean inner product.

1. Introduce a (uniform) grid in space  $x_k = -L + k\Delta x$ ,  $1 \leq k \leq K$ , where  $h = \frac{2L}{K}$ .
2. Discretize the first integral  $H$  from (1) on this grid by
  - (a) using a quadrature rule for the integral to get a discretization of the  $L_2$  inner product (a rectangular rule is sufficiently accurate and gives  $\Delta x \langle \cdot, \cdot \rangle_{\mathbb{R}^K} \approx \langle \cdot, \cdot \rangle_{L_2}$ );
  - (b) replacing the partial derivative in the integrand by finite difference quotients.

The result is a function  $H_d(\mathbf{u})$ , where  $\mathbf{u} \in \mathbb{R}^K$ . For example, in the case of the discretization of the Hamiltonian of the KdV equation we have

$$H_d(\mathbf{u}) := \Delta x \sum_{j=1}^K \left[ \left( \frac{u_{j+1} - u_j}{\Delta x} \right)^2 - u_j^3 \right]$$

$H_d : \mathbb{R}^K \rightarrow \mathbb{R}$ , and introduce  $\tilde{H}_d$  such that  $H_d = \Delta x \tilde{H}_d$  for notational convenience.

3. Compute the variational derivative of the discrete Hamiltonian  $H_d$  with respect to the discrete  $L_2$  inner product ( $\Delta x \langle \cdot, \cdot \rangle_{\mathbb{R}^K} \approx \langle \cdot, \cdot \rangle_{L_2}$ )

$$\begin{aligned} \left. \frac{d}{d\epsilon} \right|_{\epsilon=0} H_d(u + \epsilon v) &= \left. \frac{d}{d\epsilon} \right|_{\epsilon=0} \Delta x \sum_{j=1}^K \left[ \left( \frac{u_{j+1} + \epsilon v_{j+1} - (u_j + \epsilon v_j)}{\Delta x} \right)^2 - (u_j + \epsilon v_j)^3 \right] \\ &= \dots \\ &= \Delta x \langle \nabla \tilde{H}_d, v \rangle_{\mathbb{R}^K} \end{aligned}$$

where then  $\nabla \tilde{H}_d$  is the usual gradient of  $\tilde{H}_d$ , and also  $\nabla \tilde{H}_d$  is the variational derivative of  $H_d$  with respect to the discrete  $L_2$  inner product (i.e. the sought approximation of the variational derivative  $\frac{\delta H}{\delta u}$ ).

4. Discretize the operator  $\mathcal{S}$  on the grid in such a way that a skew-symmetric matrix  $S$  is obtained.
5. You now solve the system of ODEs

$$\mathbf{u}_t = S\nabla\tilde{H}_d(\mathbf{u})$$

by an integral preserving method such as the AVF method

6. Implement this in MATLAB or Python or any other choice of programming language.

Suggested parameters:  $K = 100$ ,  $L = 10$ ,  $c = 4$ ,  $h = \Delta t = 0.05$ .

**To be handed in.**

1. Document what you have done in 1–5 above, where you briefly describe how you have discretized  $H$ , your resulting  $H_d$ , write up the variational derivative of  $H_d$  with respect to the chosen discrete  $L_2$  inner product. Give your skew-symmetric matrix  $S_d$ . Which is your choice of discrete gradient, give your  $\bar{\nabla}H_d(\mathbf{u}, \mathbf{v})$ , and how does the complete method look like.
2. Supply a plot with linear axes where you show the numerical vs the exact solution at times  $t = 1$  and  $t = 50$ .
3. Also hand in a plot which shows  $H_d(\mathbf{u}^n)$  as a function of time ( $t_n = n\Delta t$ ) for  $n = 1000$  steps with stepsize  $\Delta t = 0.05$ .

**Send your answers by e-mail to [elena.celledoni@ntnu.no](mailto:elena.celledoni@ntnu.no).**