

# A Proximal-Gradient Algorithm for Crystal Surface Evolution

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joint with J.-G. Liu (Duke), J Lu (Duke), J. Marzuola (UNC), and L. Wang (Minnesota)

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# Crystal surface evolution

- Evolution of a crystal near a fixed crystallographic plane of symmetry
- $h(x,t)$  = height of crystal; facets on crystal =  $\{ x: \nabla h(x,t) = 0 \}$
- [Marzuola, Weare '13]: continuum limit of kinetic Monte Carlo models

$$E(h) = \frac{1}{p} \int |\nabla h|^p, \quad p \geq 1 \quad \partial_t h = \Delta e^{-\Delta_p h}$$

- $p=2$ , existence, uniqueness [Liu, Xu '16-'17, Xu '18, Ambrose '19,...]
- $p=1$ , numerics via microscopic SOS system [Marzuola, Weare '13]  
finite difference method [Liu, Lu, Margetis, Marzuola '17]

# Our goal:

leverage (very formal) gradient flow structure to design new numerical method

crystal growth PDE

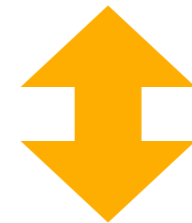
$$\partial_t h = \Delta e^{-\Delta_1 h}$$



“gradient flow”

$$\partial_t h + \nabla \cdot \left( M(h) \nabla \frac{\partial \mathcal{E}}{\partial h} \right) = 0$$

$$M(h) = e^{-\Delta_1 h}, \quad \mathcal{E}(h) = \|\nabla h\|_1$$



$$\frac{d}{dt} h(t) = -\nabla_M \mathcal{E}(h(t))$$

$$\nabla_M \mathcal{E}(h) = -\nabla \cdot \left( M(h) \nabla \frac{\partial \mathcal{E}}{\partial h} \right)$$

# Gradient flows

$$\frac{d}{dt}h(t) = -\nabla_M \mathcal{E}(h(t))$$

- $h(t)$  evolves in the direction of steepest descent of  $\mathcal{E}$ , with respect to  $M$
- $\nabla_M$  is induced by the underlying metric structure

## Gradient flow

*prof. Mark. A. Peletier, PhD*

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Examples:

- $M(h) = 1$ ,  $H^{-1}$  gradient flow
- $M(h) = h$ ,  $W_2$  gradient flow
- $M(h)$  nonnegative, concave, weighted  $W_2$  gradient flow  
[Carrillo, Lisini, Savaré, Slepčev '09, Dolbeault, Nazaret, Savaré '09, Lisini, Matthew, Savaré '19,...]
- $M(h) \in \text{Lin}(\mathbb{R}^l \times d, \mathbb{R}^l \times d)$ , gradient system [Liero, Mielke '13]

Our mobility falls well outside existing, rigorous theory of GF structure.

# Weighted $H^{-1}$ GF perspective

Suppose  $M(h) \in L^1(\mathbb{T}^d)$  is nonnegative. Define  $\Delta_h v = \nabla \cdot (M(h) \nabla v)$

- Weighted Hilbert space:  $\|v\|_{H_h^1}^2 = \int_{\mathbb{T}^d} M(h) |\nabla v|^2 = - \int_{\mathbb{T}^d} v \Delta_h v$
- Dual space:  $\|\psi\|_{H_h^{-1}}^2 = - \int_{\mathbb{T}^d} \psi \Delta_h^{-1} \psi$
- Subdifferential  $\partial_{H_h^{-1}} \mathcal{E}$ , gradient  $\nabla_{H_h^{-1}} \mathcal{E}$

To go from here to a well-defined gradient flow, need to overcome obstacles:

- time derivative of  $h(t)$  with respect to  $\|\cdot\|_{H_{h(t)}^{-1}}$
- $M(h(t))$  needs to remain integrable and nonnegative along the flow.

Then,

$$\partial_t h = -\nabla_{H_h^{-1}} \mathcal{E}(h) \iff \partial_t h + \Delta_h \frac{\partial E}{\partial h} = 0 \iff \partial_t h + \nabla \cdot \left( M(h) \nabla \frac{\partial E}{\partial h} \right) = 0$$

# Weighted $H^{-1}$ GF $\rightarrow$ Numerical Method

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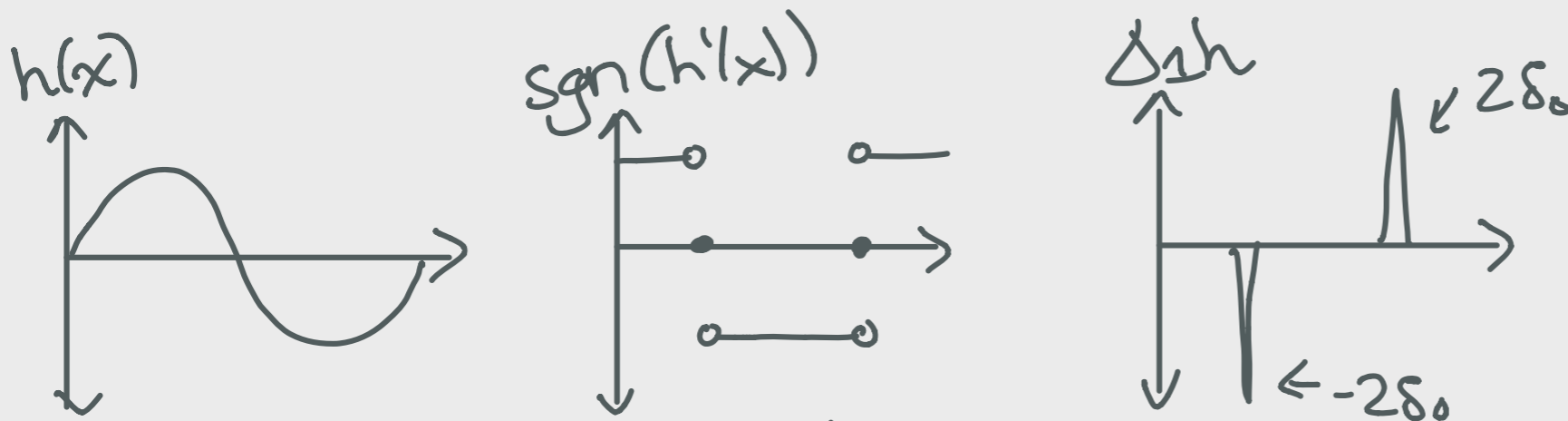
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- the mobility  $M(h) = e^{-\Delta_1 h}$  doesn't make sense, even for  $d=1$

$$\Delta_1 h = \nabla \cdot \left( \frac{\nabla h}{|\nabla h|} \right) = \nabla \cdot \text{sgn}(\nabla h)$$



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- previous work considered linearization of exponential [Giga, Giga '10,...]

$$e^x \approx 1 + x, \quad M(h) \approx 1 - \Delta_1 h$$

- we consider mollified mobility, which respects asymmetry of curvature

$$\varphi \in C_c^\infty(\mathbb{T}^d), \quad \varphi \geq 0, \quad \int_{\mathbb{T}^d} \varphi = 1, \quad \varphi_\epsilon(x) := \varphi(x/\epsilon)/\epsilon^d,$$

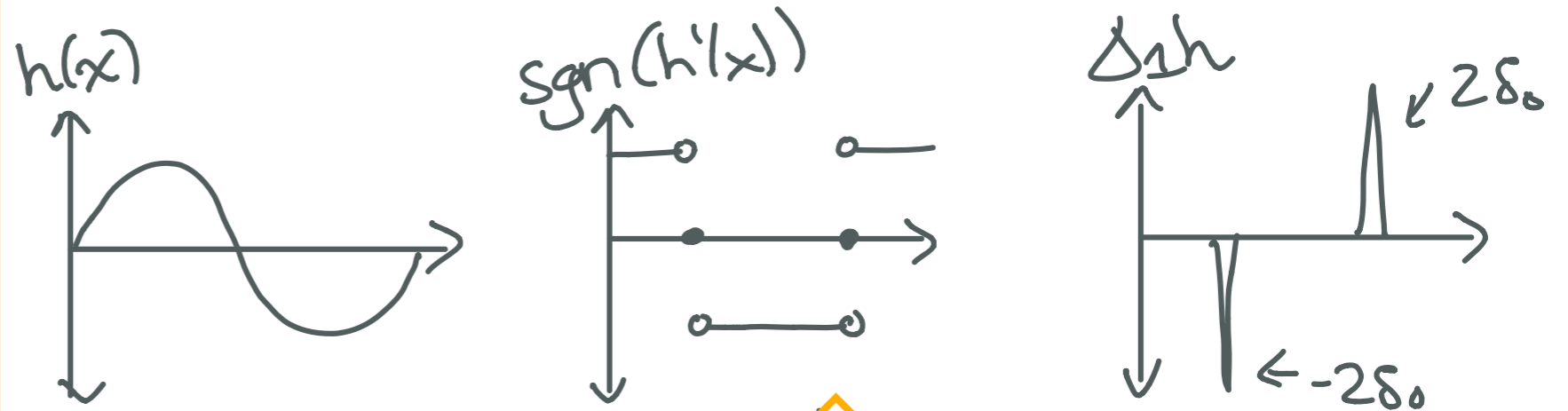
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# Weighted H<sup>-1</sup> GF -> Numerical Method

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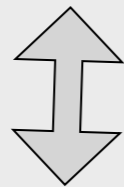
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- we consider a semi-implicit scheme (c.f. [Murphy, Walkington '19] for PME)

$$h^{n+1} \in \arg \min_h \mathcal{E}(h) + \frac{1}{2\tau} \|h - h^n\|_{H_{h^n}^{-1}}^2.$$



$$\frac{h^{n+1} - h^n}{\tau} = -\nabla \cdot \left( M(h^n) \nabla \frac{\partial \mathcal{E}}{\partial h^{n+1}} \right)$$

- for the TV energy  $E$ , if  $h^n \in D(E)$  and  $M(h^n)$  is integrable and nonnegative, there exists a unique solution  $h^{n+1}$  to our semi-implicit scheme

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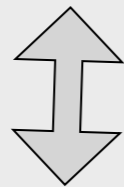
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$$h^{n+1} \in \arg \min_h \underbrace{\mathcal{E}(h) + \frac{1}{2\tau} \|h - h^n\|_{H_{h^n}^{-1}}^2}_{\| \nabla h \|_1 + \frac{1}{2\tau} \|h - h^n\|_{H_{h^n}^{-1}}^2}.$$

$$\| \nabla h \|_1 + \frac{1}{2\tau} \|h - h^n\|_{H_{h^n}^{-1}}^2 = f(Kh) + g(h)$$

$f : \mathcal{Z} \rightarrow \mathbb{R}$  convex,  $g : \mathcal{H} \rightarrow \mathbb{R}$  convex,  $K : \mathcal{H} \rightarrow \mathcal{Z}$  bounded, linear

- primal-dual algorithm! (c.f. [Laborde, Benamou, Carlier '16], [Carrillo, C., Wang, Wei '19],...)

- what is the role of the Hilbert spaces  $\mathcal{Z}, \mathcal{H}$ ?

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Which Hilbert space?

$$1) \mathcal{Z} = \mathcal{H} = L^2(\mathbb{R}^d)$$

$$2) \mathcal{Z} = L^2(\mathbb{R}^d), \quad \mathcal{H} = \dot{H}^1(\mathbb{R}^d)$$

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- [Jacobs, Léger, Li, Osher '19]
- Consider gradient descent of a smooth, convex function w/ unique min  $u_*$ .

$$F(u) = f(Ku) + g(u)$$

- Convergence rate:

$$F(u_n) \leq F(u^*) + 2L_{\mathcal{H}} \frac{\|u^* - u_0\|_{\mathcal{H}}^2}{n + 4}$$

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- Nesterov:

$$F(u_n) \leq \min_u \left[ F(u) + 4L_{\mathcal{H}} \frac{\|u - u_0\|_{\mathcal{H}}^2}{(n+2)^2} \right]$$

$$\leq \min_{\|u - u_0\|_{\mathcal{H}} \leq R} \left[ F(u) + 4L_{\mathcal{H}} \frac{\|u - u_0\|_{\mathcal{H}}^2}{(n+2)^2} \right]$$

$$\leq F(u_*) + 4L_{\mathcal{H}} \frac{R^2}{(n+2)^2} + \underbrace{\min_{\|u - u_0\|_{\mathcal{H}} \leq R} F(u) - F(u_*)}_{\delta_F(R)}$$

Thus, one can get around  $\|u_* - u_0\|_{\mathcal{H}} = +\infty$ , as long as  $\delta_F(R) \rightarrow 0$ .

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- [Jacobs, Léger, Li, Osher '19]
- Analogous result holds for Chambolle-Pock's PDHG method (nonsmooth):

$$u_{n+1} = \arg \min_{u \in \mathcal{H}} g(u) + (u, K^T \bar{p}_n)_{\mathcal{H}} + \frac{1}{2\lambda} \|u - u_n\|_{\mathcal{H}}^2,$$

$$p_{n+1} = \arg \max_{p \in \mathcal{Z}} -f^*(p) + (K u_{n+1}, p)_{\mathcal{Z}} - \frac{1}{2\sigma} \|p - p_n\|_{\mathcal{Z}}^2,$$

$$\bar{p}_{n+1} = 2p_{n+1} - p_n.$$

for  $u^N = \frac{1}{N} \sum_{n=1}^N u_n$  and  $\lambda\sigma \|K^T K\|_{\mathcal{H}}^2 < 1$ , we have

$$F(u_N) \leq F(u_*) + C \frac{R}{N} + \underbrace{\min_{\|u - u_0\|_{\mathcal{H}} \leq R} F(u) - F(u_*)}_{\delta_F(R)}$$



# Numerical method for crystal evolution

- Outer time iteration:

$$h^{n+1} = \operatorname{argmin}_h \mathcal{E}(h) + \frac{1}{2\tau} \|h - h^n\|_{H_{h^n}^{-1}}^2$$

- Inner time iteration: for  $\lambda\sigma < 1$ ,

$$h^{(m+1)} = \left( \frac{\tau}{\lambda} \Delta_{h^n} \Delta + \operatorname{id} \right)^{-1} \left( \frac{\tau}{\lambda} \Delta_{h^n} \Delta h^{(m)} - \tau \Delta_{h^n} \nabla \cdot \phi^{(m)} + h^n \right)$$

$$\bar{h}^{(m+1)} = 2h^{(m+1)} - h^{(m)}$$

$$\phi^{(m+1)} = (\operatorname{id} + \sigma \partial F^*)^{-1} (\phi^{(m)} + \sigma \nabla \bar{h}^{(m+1)}),$$

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Benefits:

- avoids inverting 1-Laplacian
- freedom to choose  $\lambda$  large helps with computation of  $h^{(m+1)}$

# Convergence of PDHG

**Theorem:** [CMLLW '20] Let  $d=1$ . Suppose the PDHG algorithm is initialized with

$$h^{(0)} = h^n, \phi^{(0)} = 0,$$

Then for all  $\delta > 0$ , there exist  $\tilde{M}, \lambda, \sigma$ , so that

$$F(h^{(M)}) - F(h^{n+1}) \leq \delta, \quad \forall M \geq \tilde{M}, \quad F(h) = \mathcal{E}(h) + \frac{1}{2\tau} \|h - h^n\|_{H_{h^n}^{-1}}^2$$

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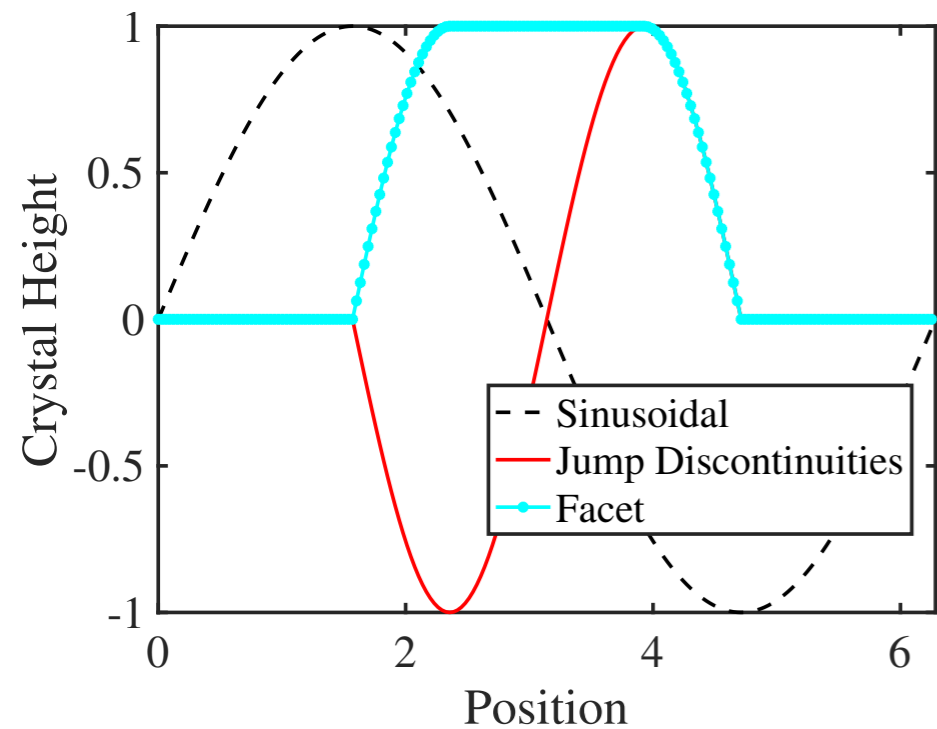
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Remarks:

- Extends to general  $M(h)$  provided that  $M(h^n)$  and  $1/M(h^{n+1})$  integrable [c.f. Cancés, Gallouët, and Todeschi '19]
- We require  $d=1$  to conclude  $\|h^n\|_\infty \leq \mathcal{E}(h^n) < +\infty$ . Higher integrability of  $1/M(h^{n+1})$  would be required to weaken this assumption.
- If one has  $\nabla h^n \in \text{BV}$ , quantitative estimates:  $\tilde{M} \sim \delta^{-2}, \lambda \sim \delta^{-1}, \sigma \sim \delta$
- Key step:  $\delta_F(R) = \min_{\|h^n - h\|_{\dot{H}^1} \leq R} F(h) - F(h^{n+1}) \xrightarrow{R \rightarrow +\infty} 0$

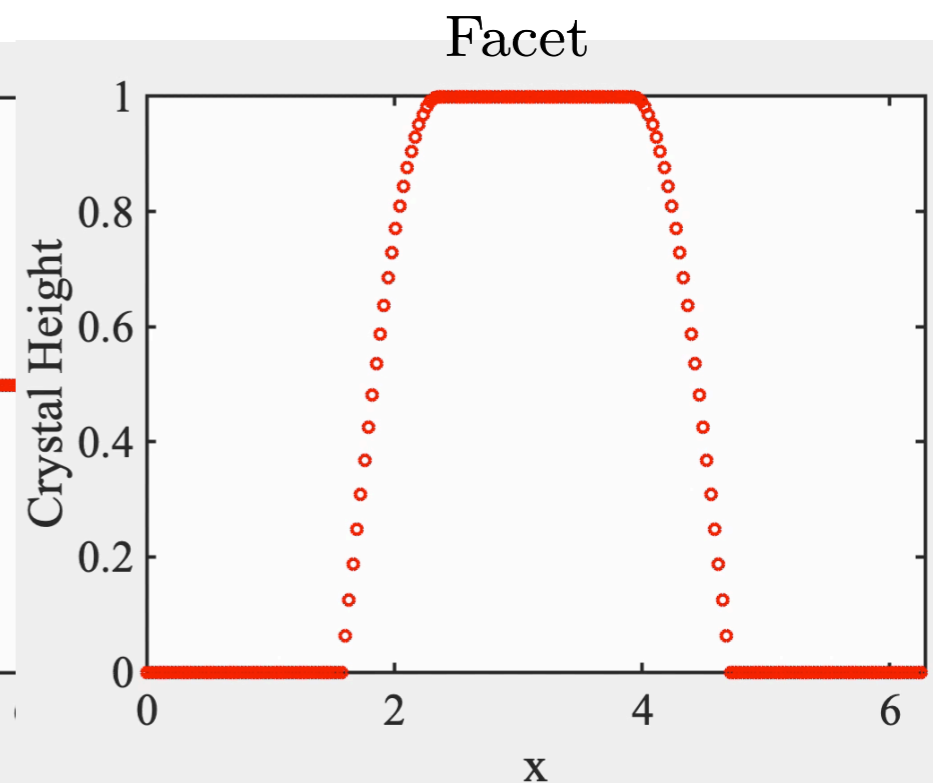
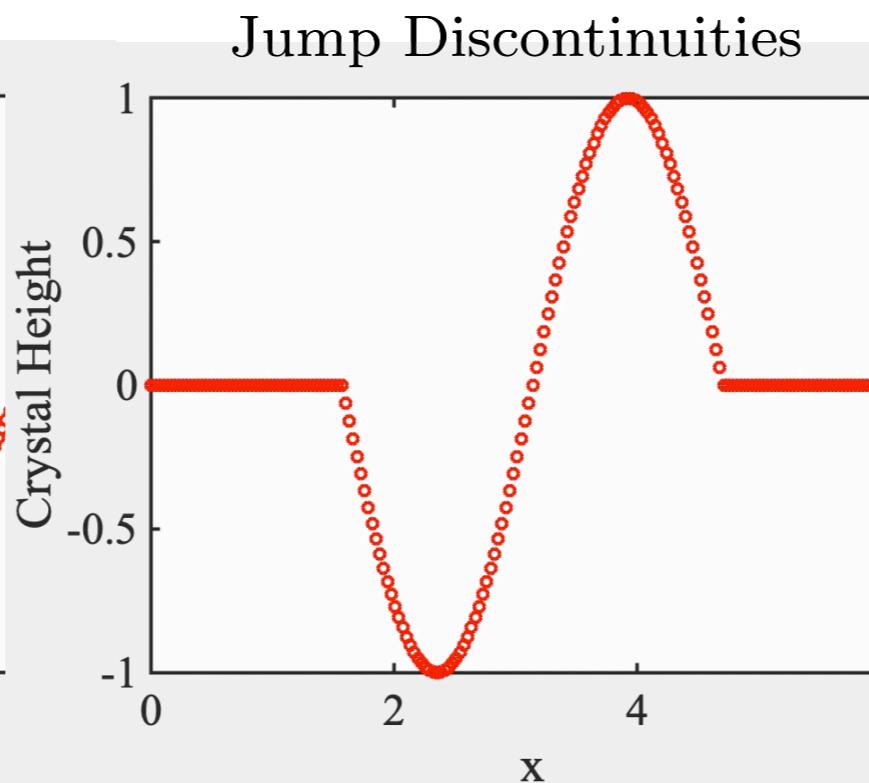
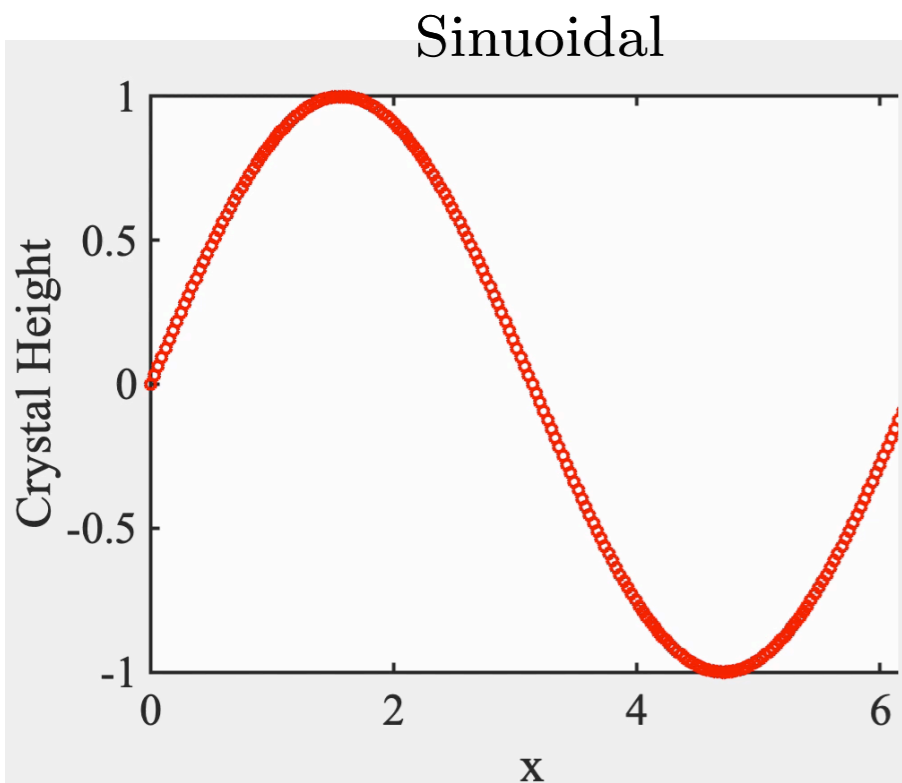
# Numerical Results: dynamics



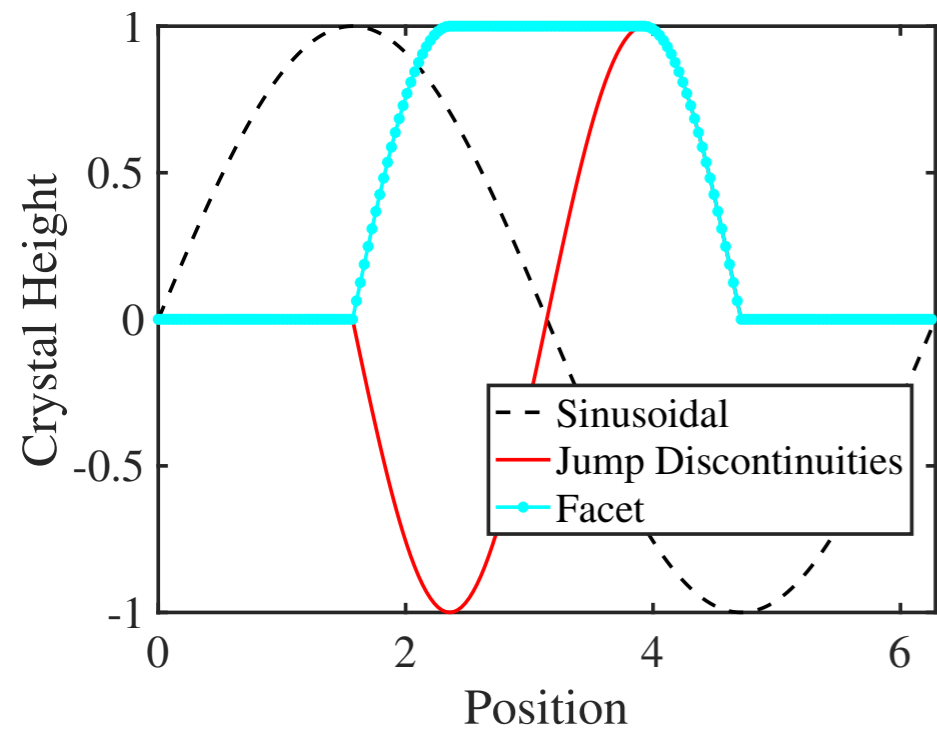
Observations:

- facet formation at local maxima
- pinning at local minima

$N_x = 200$ ,  $N_t = 10$ ,  $\sigma = 0.0005$ ,  $\lambda = 500$ ,  $\varepsilon = 0.04$



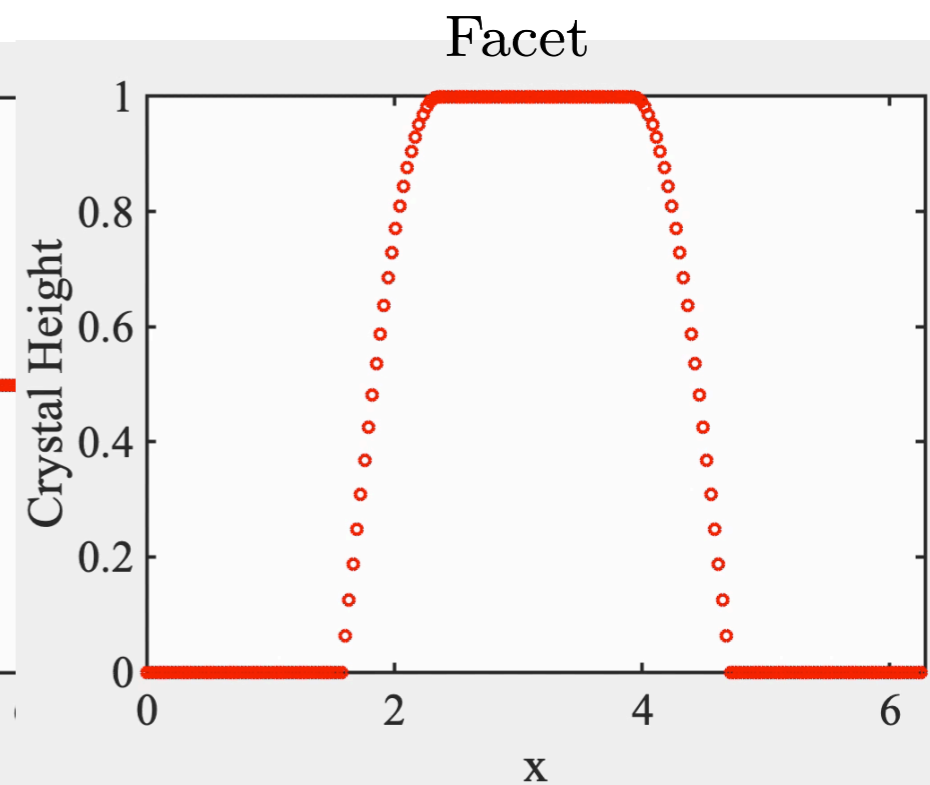
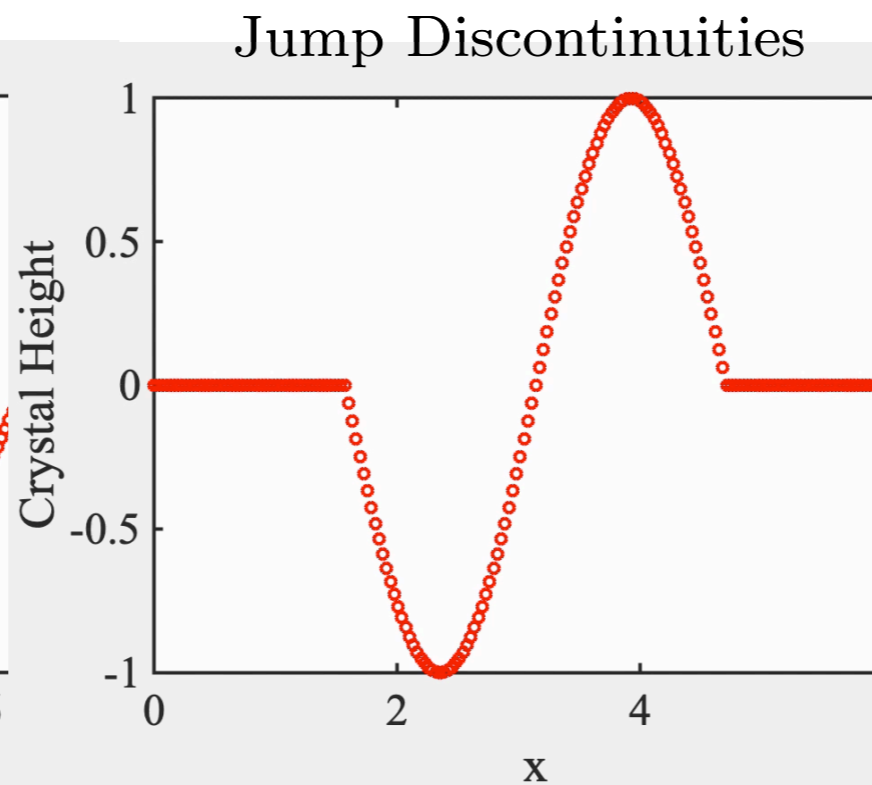
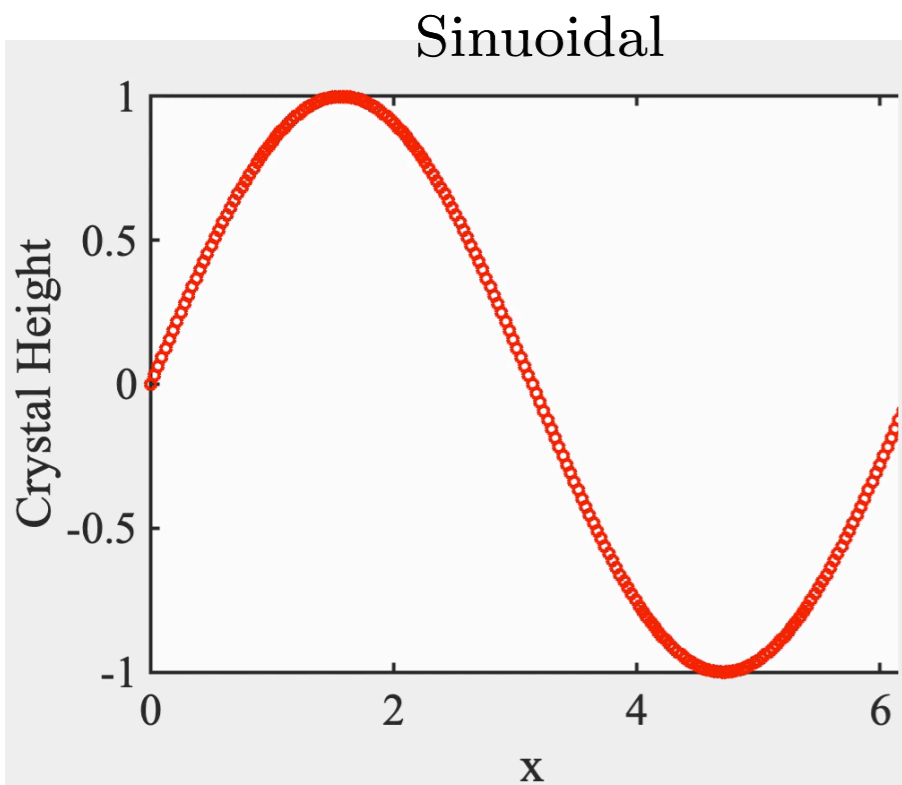
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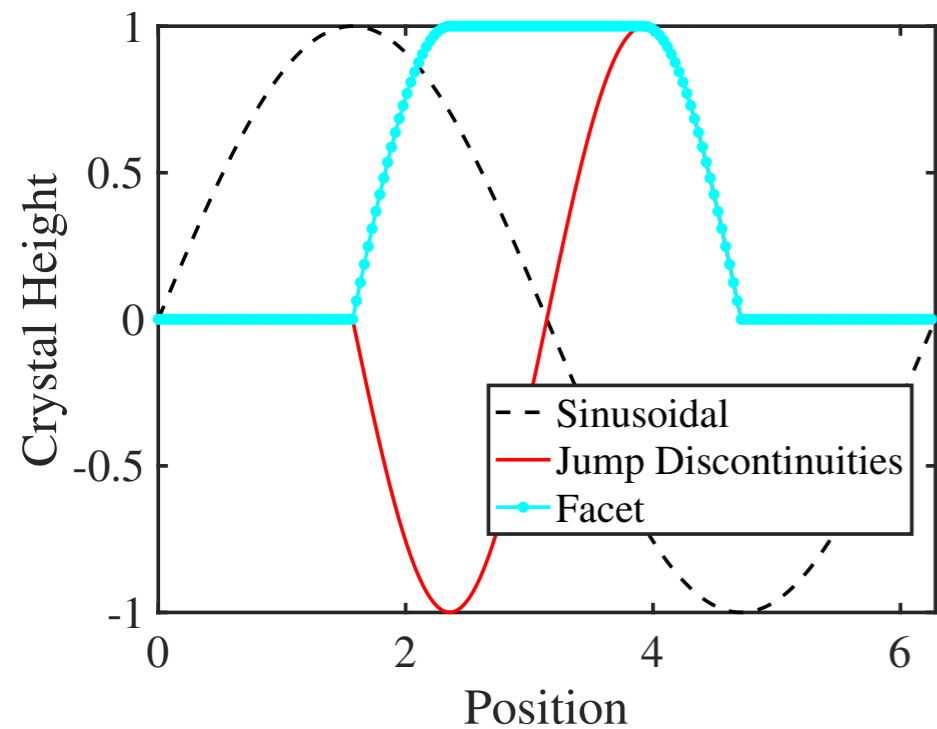
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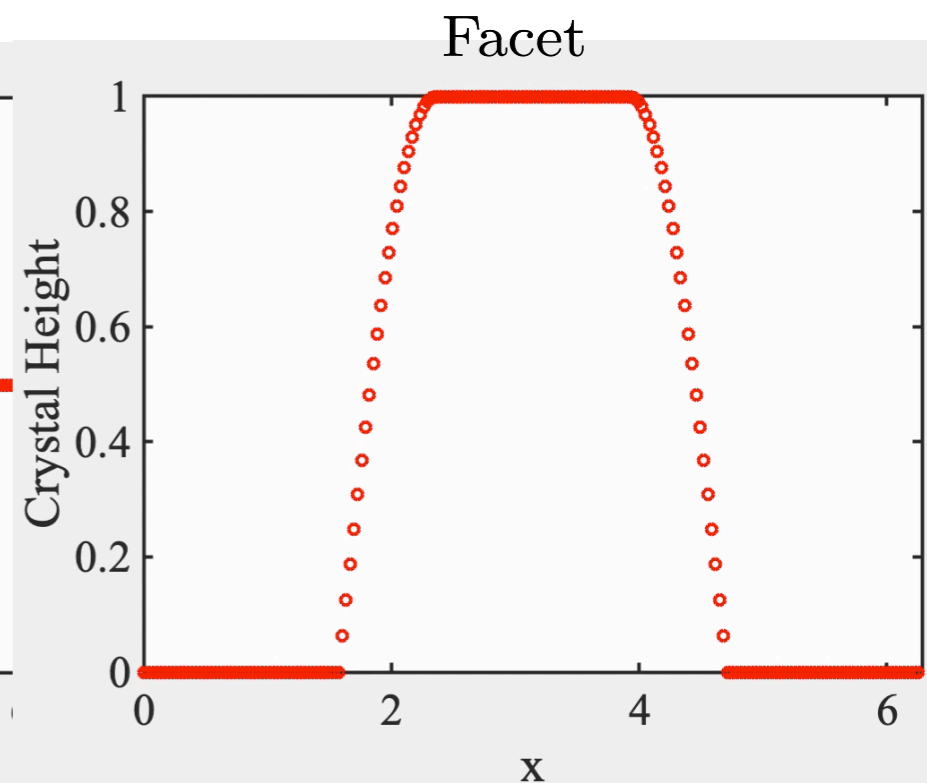
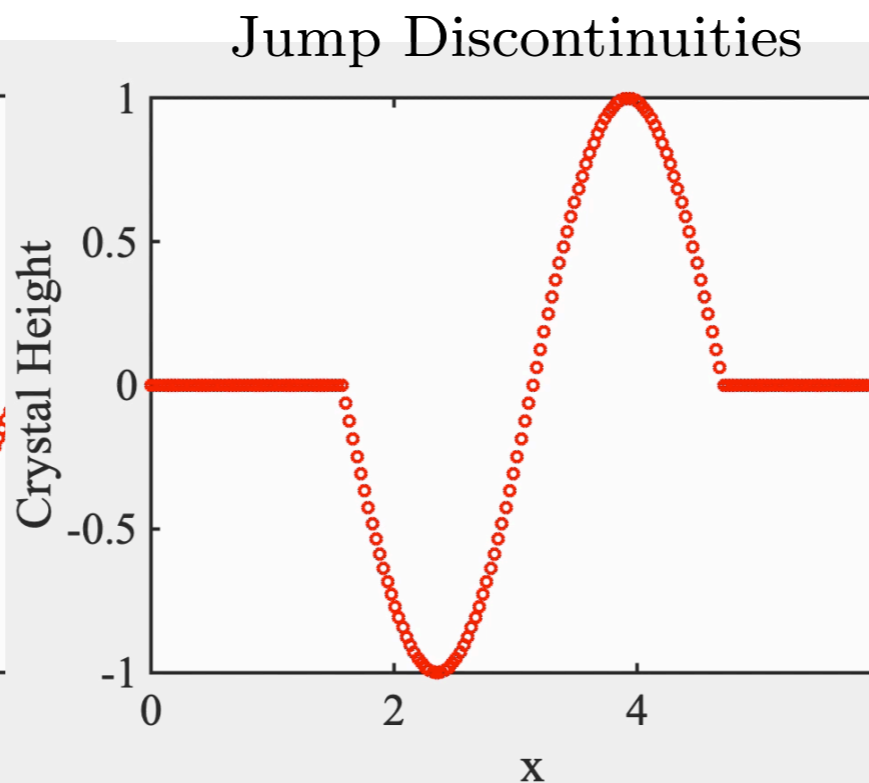
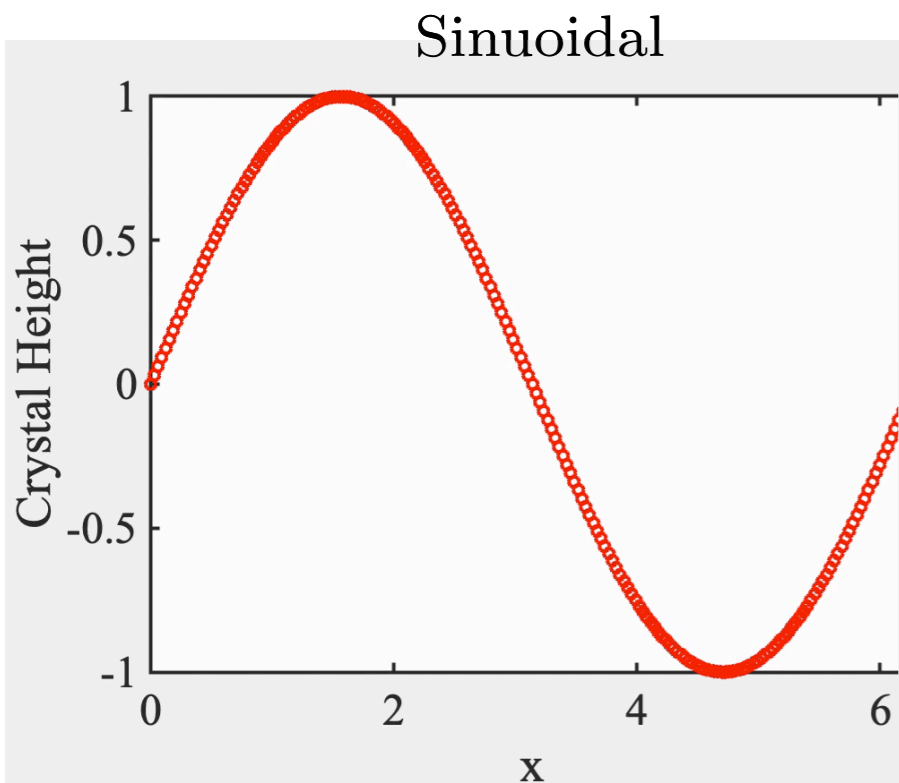
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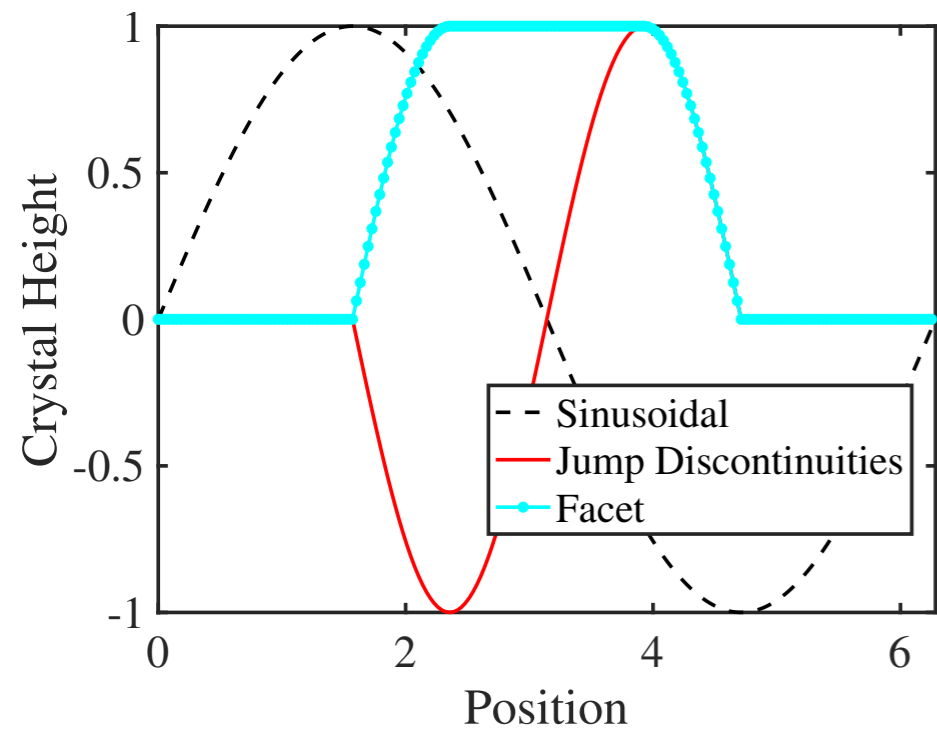
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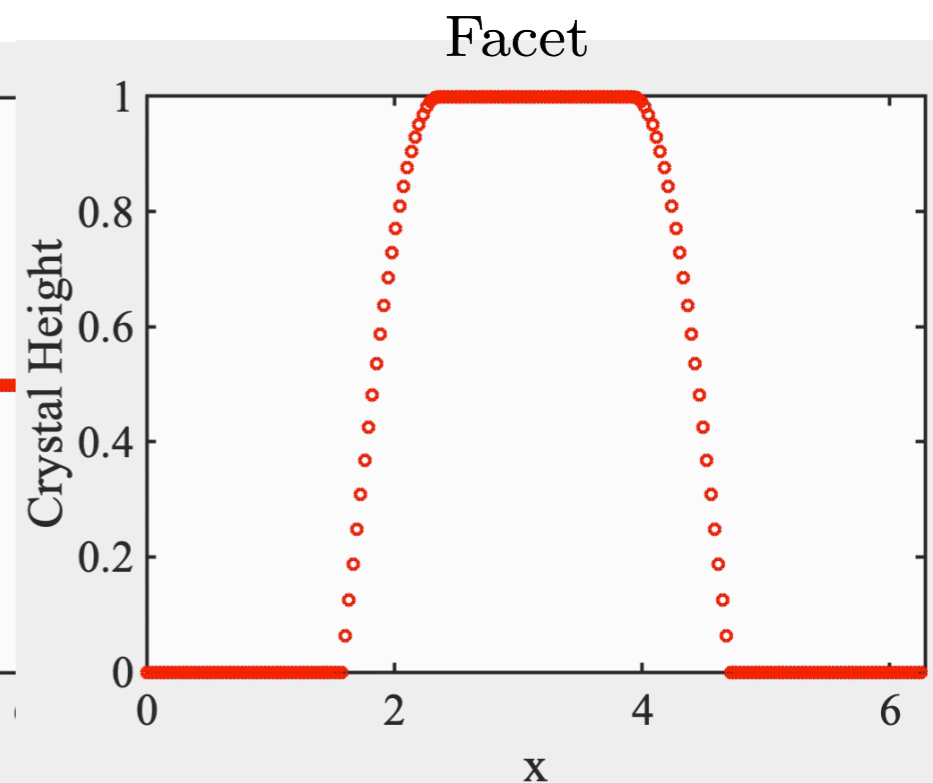
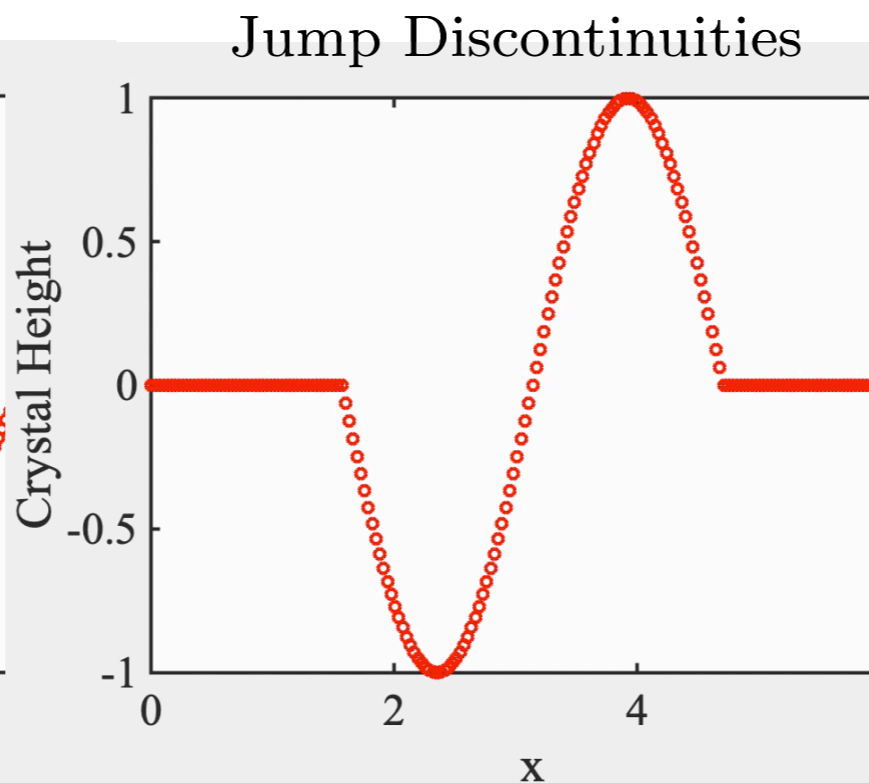
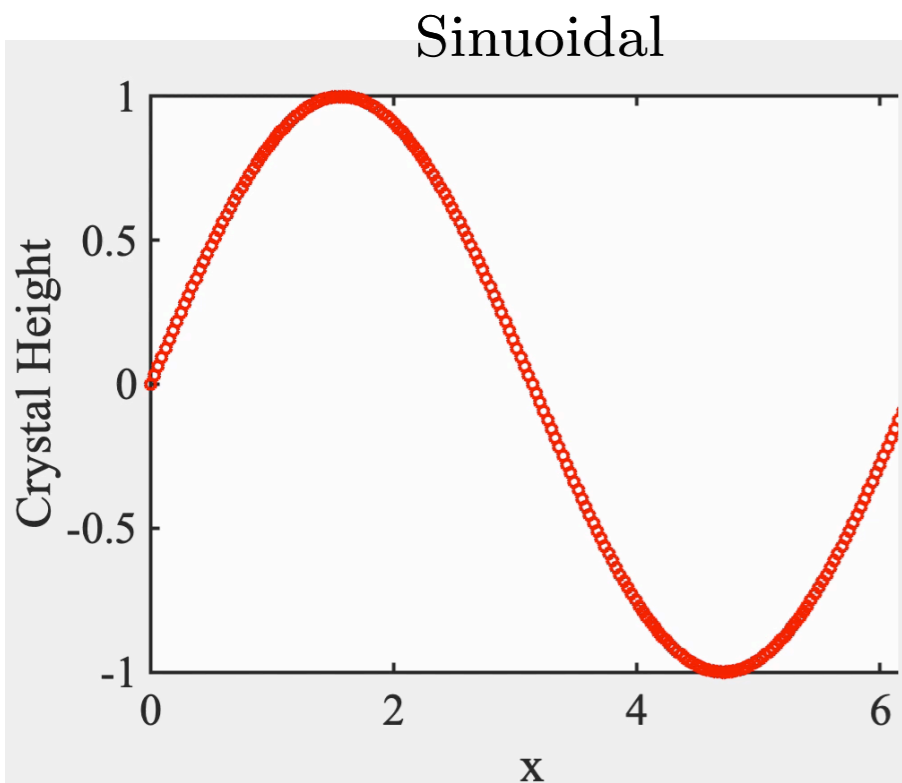
# Numerical Results: dynamics



Observations:

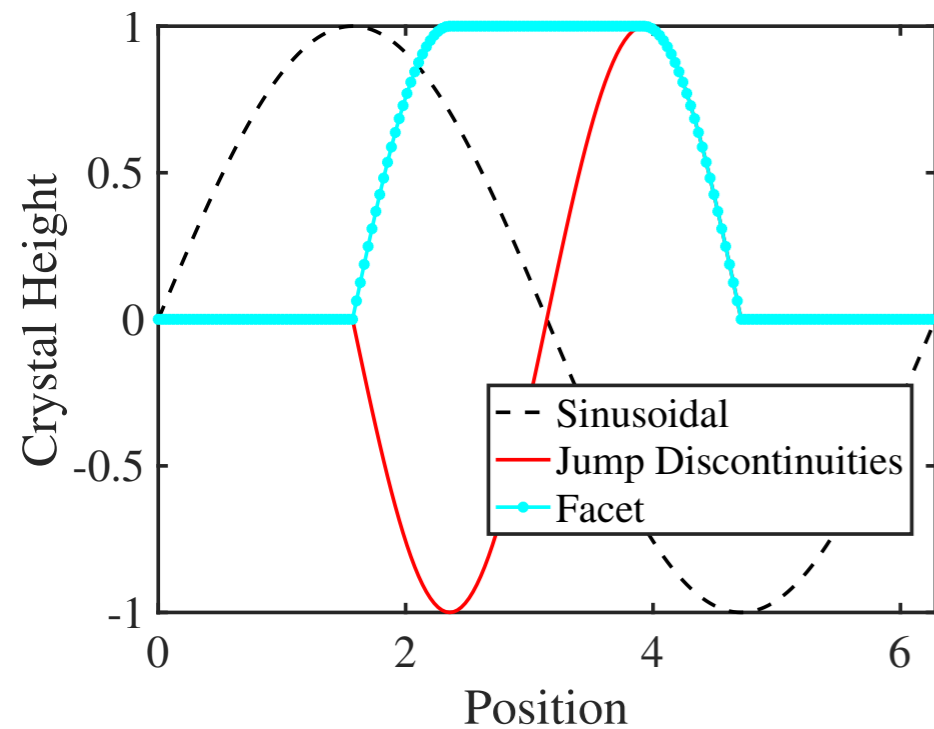
- facet formation at local maxima
- pinning at local minima

$N_x = 200$ ,  $N_t = 10$ ,  $\sigma = 0.0005$ ,  $\lambda = 500$ ,  $\varepsilon = 0.04$





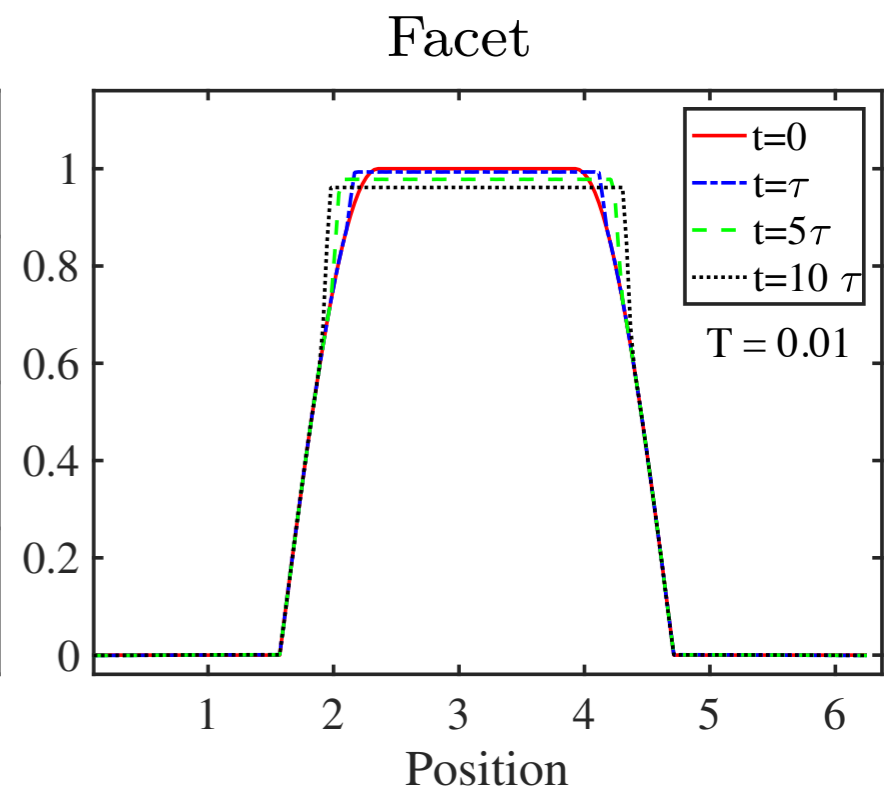
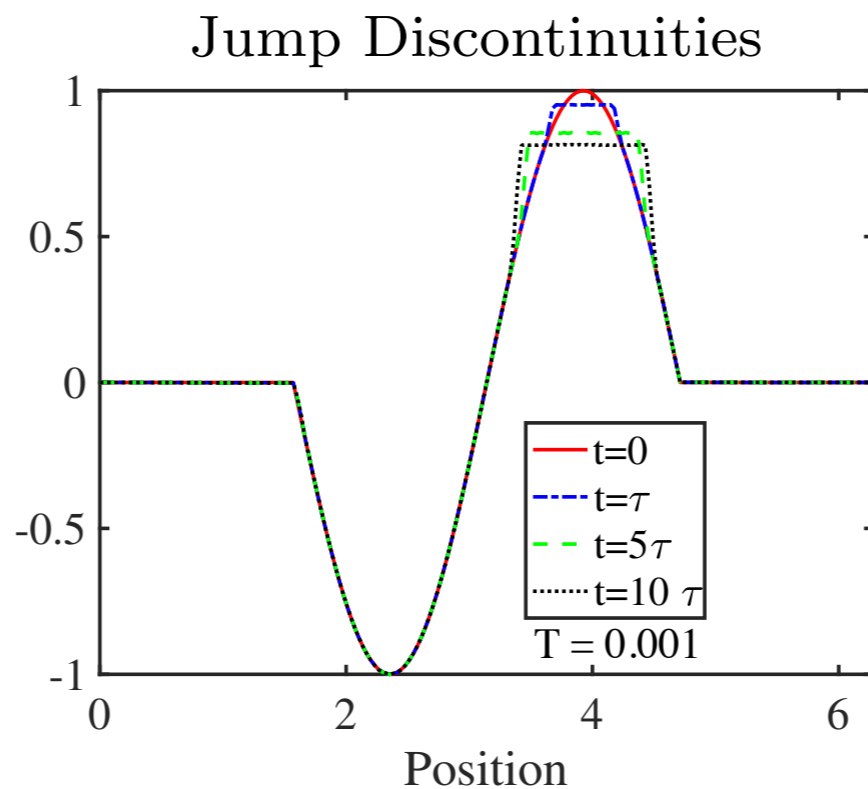
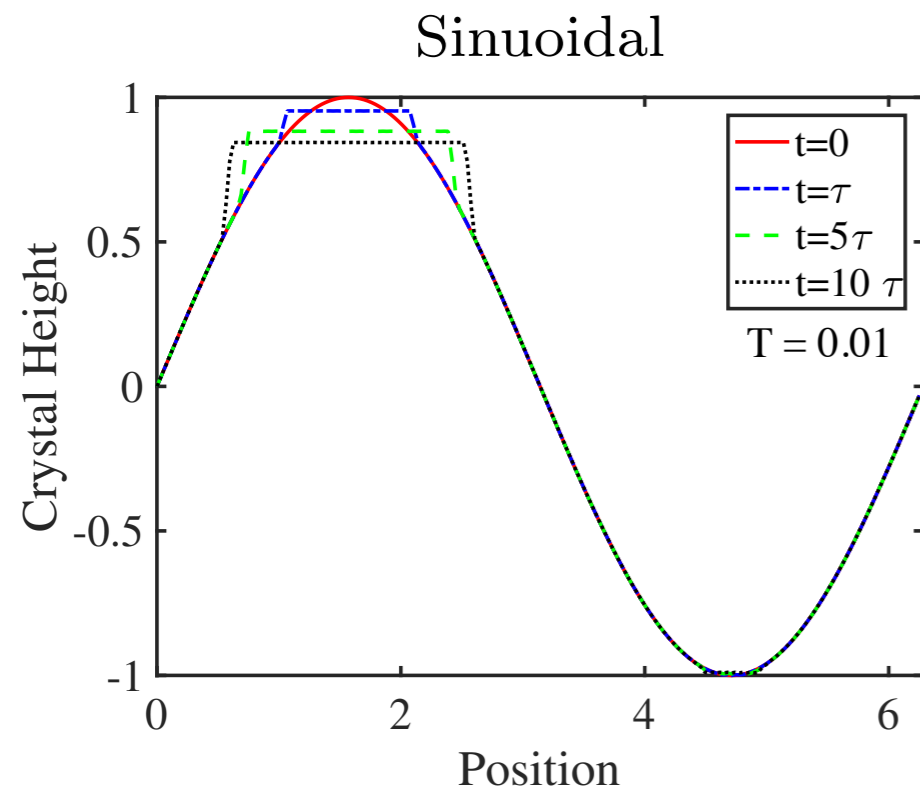
# Numerical Results: dynamics



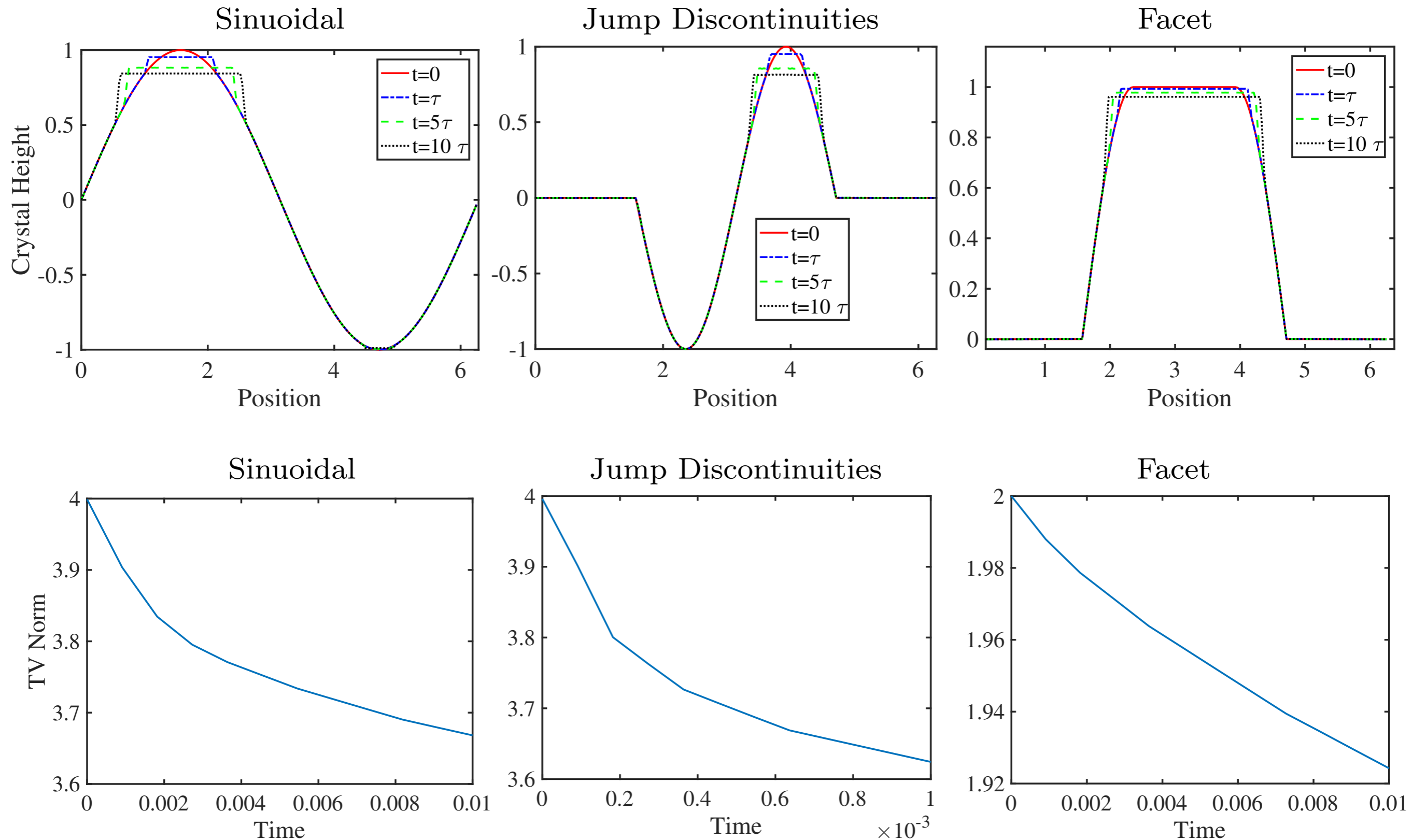
Observations:

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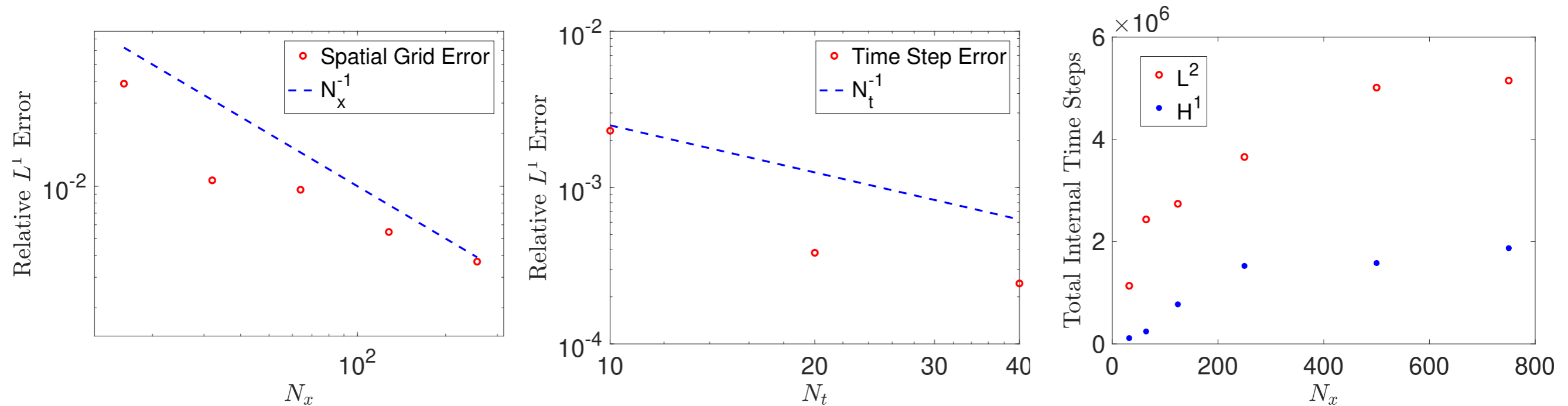
$N_x = 200$ ,  $N_t = 10$ ,  $\sigma = 0.0005$ ,  $\lambda = 500$ ,  $\varepsilon = 0.04$



# Numerical Results: energy decrease



# Numerical Results: convergence



## Observations:

- Error vs  $N_x$ : slightly sublinear convergence (low spatial regularity)
- Error vs  $N_t$ : first order (semi-implicit Euler)
- Internal time steps vs  $N_t$ : importance of selecting correct Hilbert space

sinusoidal, ( $N_x = 200$ ), ( $N_t = 10$ ),  $\sigma = 0.0005$ ,  $\lambda = 500$ ,  $\varepsilon = 0.05$ ,  $T = 10^{-4}$

# Open questions

## crystal growth PDE

$$\partial_t h = \Delta e^{-\Delta_1 h}$$

## “gradient flow”

$$\partial_t h = -\nabla_{H_h^{-1}} \mathcal{E}(h)$$

$$M_\epsilon(h) = e^{-\varphi_\epsilon * \Delta_1 h}, \quad \mathcal{E}(h) = \|\nabla h\|_1$$

## discrete time scheme

$$h^{n+1} = \operatorname{argmin}_h \mathcal{E}(h) + \frac{1}{2\tau} \|h - h^n\|_{H_{h^n}^{-1}}^2$$

## PDHG scheme

$$h^{(m+1)} = \left( \frac{\tau}{\lambda} \Delta_{h^n} \Delta + \operatorname{id} \right)^{-1} \left( \frac{\tau}{\lambda} \Delta_{h^n} \Delta h^{(m)} - \tau \Delta_{h^n} \nabla \cdot \phi^{(m)} + h^n \right)$$

$$\bar{h}^{(m+1)} = 2h^{(m+1)} - h^{(m)}$$

$$\phi^{(m+1)} = (\operatorname{id} + \sigma \partial F^*)^{-1} (\phi^{(m)} + \sigma \nabla \bar{h}^{(m+1)}),$$

# Open questions

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Today: Convergence of PDHG,  
E TV energy, gen  $M(h)$ ,  $d=1$

# Open questions

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- Convergence as  $\tau \rightarrow 0$ ?
- Convergence as  $\tau, \epsilon \rightarrow 0$ ?

Today: Convergence of PDHG,  
E TV energy, gen  $M(h)$ ,  $d=1$

# Open questions

## crystal growth PDE

$$\partial_t h = \Delta e^{-\Delta_1 h}$$

- Appropriate notion of weak solution?
- Better time discretization/GF formulation to prove existence of wider class of weak solutions? numerics?

## “gradient flow”

$$\partial_t h = -\nabla_{H_h^{-1}} \mathcal{E}(h)$$

$$M_\epsilon(h) = e^{-\varphi_\epsilon * \Delta_1 h}, \quad \mathcal{E}(h) = \|\nabla h\|_1$$

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Today: Convergence of PDHG,  
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Thank you!