Can we tame earthquakes?

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Anti-lock Braking System
Earthquakes and faults
Greendale fault, New Zealand
Greendale fault, New Zealand
Earthquakes in simple words
Earthquakes in simple words

Far field tectonic displacements (~cm/yr), \( u_\infty = v_\infty t \)

Fault

Friction (F)

\(-u_\infty = -v_\infty t\)

Storage of elastic energy in the crust \( U_{el} \uparrow \)
Earthquakes in simple words

Far field tectonic displacements (~cm/yr), $u_\infty = v_\infty t$

Fault

Fault

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Storage of elastic energy in the crust $U_{el}$
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$-u_\infty = -v_\infty t$

Storage of elastic energy in the crust $U_{el} \uparrow$
Earthquakes in simple words

Instability

Far field tectonic displacements (~cm/yr), $u_\infty = v_\infty t$

Friction (F)

$-u_\infty = -v_\infty t$

Fault

$\delta$

Earthquakes in simple words

Instability

Far field tectonic displacements (~cm/yr), $u_\infty = v_\infty t$

Friction (F)

$-u_\infty = -v_\infty t$

Fault

$\delta$
Injecting fluids and friction

\[ F = \mu \cdot N \]
Injecting fluids and friction

\[ F = \mu \cdot (N - P_f) \]
Injecting fluids and friction

\[ F = \mu \cdot (N - P_f) \]
Injecting fluids and friction

\[ F = \mu \cdot (N - P_f) \]

[Terzaghi, 1925]
Increasing complexity: Burridge-Knopoff & Faults

1D B-K model

2D B-K model

A fault
Increasing complexity: Burridge-Knopoff & Faults

1D B-K model

\[ \dot{x} = f(x, p_f, t) \]

2D B-K model

A fault
The mathematical theory of control
The mathematical theory of control

Physical process of earthquakes
The mathematical theory of control
The mathematical theory of control

Fluid pressure

Physical process of earthquakes

Designed Controller

\[ u_1(t) \quad + \quad u(t) \quad + \quad y(t) \]

\[ y_e(t) \quad + \quad u_2(t) \]

\[ \Sigma(P) \quad \Sigma(C) \]
The mathematical theory of control

Target: stabilization, tracking, optimization & robustness
Robust non-linear control

If:

1) The friction coefficient is Lipschitz continuous w.r.t the states $x$:

$$|\mu(x, t) - \mu(0)| < \beta |x|, \beta > 0$$

2) The friction coefficient has a lower bound: $\mu(x, t) > c > 0$

3) Elasticity and viscosity of the surrounding rocks are bounded

4) Diffusivity has a lower bound greater than zero

then we can design an output feedback stabilizing controller and we can achieve asymptotic tracking.

[Stefanou, 2020, pre-print
Stefanou & Tzortzopoulos, 2021, submitted
Tzortzopoulos & Stefanou, under preparation]
Example of control of a complex frictional system

[see also Turcotte, 1992, – among many others]
Example of control of a complex frictional system

[see also Turcotte, 1992, among many others]
Stock markets?

[Gabaix, X. 2009]

\[1 + \zeta_q = 2.5\]
Tracking and global stabilization
Tracking and global stabilization

Deactivation of the controller

Stable equilibrium

Control
Strike-slip fault with Rate & State friction

\[ a, b, d_c \text{ distributed over the fault area according to a log-normal distribution} \]
Without control (open loop)
Earthquake control with Reinforcement Learning

Deep Reinforcement Learning

Training

Highest Expected Return ➔ Optimal Policy
DRL, discrete time dynamics & results

Displacement

\[ \frac{y}{d_{\text{max}}} \]

Velocity

\[ \frac{y}{V_{\text{inst}}} \]

Pressure

\[ \Delta P_1 (\text{MPa}) \]
Conclusions

Earthquake Control?

Impossible?

mathematics mechanics physics experiments

Adjacent possible?
Thank you!

George Tzortzopoulos-Marinis
Philipp Braun
Alexandros Stathas
Filippo Masi
Timos Papachristos

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TEDx Talk: https://youtu.be/9JXdv-3e2bc

www.coquake.eu
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Diego Guttiérez-Oribio
Pravin Badarayani
Thank you!

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Greendale fault, New Zealand

NO FAULT HERE

yeah right
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BRIDGING THE SCALES

Systems involving complex materials — multiple inherent scales

(Rattez et al, JMPS, 2018a,b)
(Collins et al, JMPS, 2020)

(Robinet et al, WRR, 2012)
BRIDGING THE SCALES – MULTISCALE MODELING

atomistic

(Szost et al, Mat Des, 2013)

microscopic

(Robinet et al, WRR, 2012)

mesoscopic

(Rattez et al, JMPS, 2018)

macroscopic

μm

mm

cm

km
BRIDGING THE SCALES – MULTISCALE MODELING

boundary value problem

ΔΣ

ΔE

FE²
FEM×DEM
FEM×…

auxiliary problem

(slow)
BRIDGING THE SCALES – DATA-DRIVEN MODELING

MACRO

\[ \Delta \Sigma \]

boundary value problem

\[ \Delta E \]

auxiliary problem

MICRO

\[ \Delta \Sigma \]

(data-driven & machine learning)

\[ \Delta \Sigma \]

(data)

(fast)

(slow)
BRIDGING THE SCALES – TANN

MACRO

$\Delta \Sigma$

FEM×TANN

boundary value problem

$\Delta \Sigma$

MICRO

Thermodynamics-based Artificial Neural Networks

$\frac{\partial \psi}{\partial E}$

physics (fast & reliable)

data

(auxiliary problem)

(slow)
Clausius-Duhem inequality (local)

\[ d = s : \dot{f} - \dot{\psi} - \eta \dot{\theta} \geq 0 \]

\[ d \text{ mechanical dissipation rate} \]
\[ s \text{ 1}^{\text{st}} \text{ Piola-Kirchhoff stress} \]
\[ f \text{ deformation gradient} \]
\[ \psi \text{ free-energy} \]
\[ \eta \text{ entropy} \]
\[ \theta \text{ absolute temperature} \]

Clausius-Duhem inequality (volume average)

\[ D = S : \dot{F} - \dot{\Psi} - H^{\dagger} \dot{\Theta} \geq 0 \]

with \[ Y = \langle y \rangle = \frac{1}{|V|} \int_{V} y \, dx \] and \[ \langle \eta \dot{\theta} \rangle = H^{\dagger} \dot{\Theta} \]
STATE SPACE \( (t) = \{\chi(t), Z(t)\} \)

state variables: observable \( \chi = \{\Theta, F\} \) and internal \( Z = \{?\} \)

state functions: \( \Psi (\chi, Z) \quad S (\chi, Z) \quad H^\dagger (\chi, Z) \quad D (\chi, Z, \dot{Z}) \)

time differentiation: \( \dot{\Psi} = \frac{\partial \Psi}{\partial \Theta} \dot{\Theta} + \frac{\partial \Psi}{\partial F} : \dot{F} + \sum_{k=1}^{N_{ISV}} \frac{\partial \Psi}{\partial Z_k} \cdot \dot{Z}_k \)

THERMODYNAMIC RESTRICTIONS:

stress: \( S = \frac{\partial \Psi}{\partial F} \)

dissipation rate: \( D = - \sum_{k=1}^{N_{ISV}} \frac{\partial \Psi}{\partial Z_k} \cdot \dot{Z}_k \geq 0 \)

entropy: \( H^\dagger = \frac{\partial \Psi}{\partial \Theta} \)
state at $t + \Delta t = \text{TANN}\{\text{state at } t, \Delta F^t\}$

\[
\mathcal{L}(\mathcal{O}) = \frac{1}{N} \sum_{i=1}^{N} \ell(o_i)
\]

\[
\ell(o_i) = ||\tilde{o}_i - o_i||_1
\]

HYPER- AND HYPO-PLASTICITY

STATE VARIABLES?

**internal coordinates**

microscopic state space: displacement, velocity, momentum fields, etc.

THERMODYNAMICS-BASED ARTIFICIAL NEURAL NETWORKS

\[ \ell = \lambda^\xi \left[ \ell(\xi^t) + \ell(\xi^{t+\Delta t}) \right] + \lambda^{\nabla_{ED}} \ell(\nabla^t_{ED}) + \lambda^\Psi \ell(\Psi) + \lambda^{\Delta S} \ell(\Delta S) + \lambda^D \ell(D) \]

\[ \ell = \lambda \dot{Z} \ell(\dot{Z}) + \lambda \psi \ell(\psi) + \lambda^{\Delta S} \ell(\Delta S) + \lambda^D \ell(D) \]

BENCHMARKS FOR LATTICE STRUCTURES

Inelastic lattice cells

\[ \Sigma = \langle \sigma \rangle = \frac{1}{|V|} \sum_{k}^{N_{\text{nodes}}} t_{k} \otimes y_{\Delta k}^{p} \]

\[ E = \langle \varepsilon \rangle = \frac{1}{|V|} \int_{\partial V} u \otimes x \, ds \]

- training on micromechanical datasets generated from random loading paths

<table>
<thead>
<tr>
<th>unit cells</th>
<th>average behavior</th>
<th>state variables</th>
<th>internal coordinates</th>
<th>computational cost</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \Sigma_{11} ) (MPa)</td>
<td>( E_{11} ) (-)</td>
<td>( \Psi ) (kN.m)</td>
<td>( f ) (kN)</td>
</tr>
<tr>
<td></td>
<td>[Graph]</td>
<td>[Graph]</td>
<td>[Graph]</td>
<td>[Graph]</td>
</tr>
<tr>
<td></td>
<td>-5000 to 5000</td>
<td>-0.01 to 0.01</td>
<td>-0.1 to 0.1</td>
<td>increments 100</td>
</tr>
</tbody>
</table>

\( \text{ACCURACY} \geq 99\% \quad \text{---} \quad \text{ACCELERATION} \approx 10^{3} \)
THE FEM x TANN APPROACH

large-scale problem
THE FEM × TANN APPROACH

large-scale problem

ΔE

ΔΣ

Thermodynamics-based Artificial Neural Networks

Gauss point

state variables
THE FEM × TANN APPROACH

Large-scale problem

\[ \Delta E \]

Thermodynamics-based Artificial Neural Networks

\[ \Delta \Sigma \]

Gauss point

State variables

Microstructure

Macroscale approach

Microscale approach
APPLICATION TO LARGE-SCALE PROBLEMS

FEM×TANN  microscopic

- Graphs showing $u(0)$, $u(0) + \epsilon u^{(1)}$, $u^\epsilon$, $D_{tot}$, $D^\epsilon_{tot}$, $\Psi_{tot}$, and $\Psi^\epsilon_{tot}$ as functions of $1/\epsilon$. 

[Graphs illustrating the relationship between $u$, $D$, and $\Psi$ with respect to $1/\epsilon$.]
APPLICATION TO LARGE-SCALE PROBLEMS

\[ \Omega = 0^\circ \quad \Omega = 30^\circ \quad \Omega = 50^\circ \quad \Omega = 60^\circ \]

\[ D (\text{kNm/s}) \]

\[ u (\text{cm}) \]

\[ u^{(0)} + \epsilon u^{(1)} \]

\[ u^{\varepsilon} \]

\[ D_{\text{tot}} \quad D_{\text{tot}}^{\varepsilon} \]

vertical displacement
\[ \begin{array}{c} 2 \ 1 \ 0 \\ \text{(cm)} \end{array} \]

unloading
APPLICATION TO LARGE-SCALE PROBLEMS
APPLICATION TO GRANULAR MEDIA

encoding the microscopic state space
CONCLUSIONS

Earthquake control?

TANN
- digital twins
- ++ complex materials

CoQuake.com

Impossible

Adjacent possible?
ACKNOWLEDGMENTS

www.coquake.eu
www.blastructures.eu
youtu.be/p6UJ03P6LUY

RELATED ARTICLES


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