GPU-accelerated Multiphysics-based Seismic Wave Propagation Simulation and its Surrogate Model with Machine Learning

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Introduction

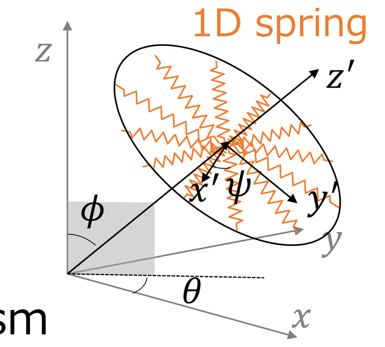
Multiphysics-based earthquake simulation
- is expected to contribute to estimation and mitigation of earthquake damage
- entails high computational cost especially in 3D simulation

GPU-accelerated method
- We developed a high-performance method for seismic wave propagation simulation with finite element method (FEM) considering a complex multiphysics phenomenon, soil liquefaction [1]
- Load balancing scheme that considers GPU architecture and characteristics of soil liquefaction simulation was adopted
- A 10.7-fold speed up over CPU-based implementation was achieved

Neural network based surrogate model
- HQC (high quality computing) considering uncertainty of information (e.g., soil properties, ground structure) is important
  → Many cases of 3D simulation are required
- Not realistic to perform 3D simulation for hundreds times, even with the developed method
- We constructed a neural network (NN) based surrogate model to enable faster judgement of soil liquefaction with over 90% accuracy

Multiphysics-based Simulation

Multiphysics Problem
- Complex dynamic multiphysics problem in which soil behaves highly nonlinearly as it gets liquefied and phase transition from solid to liquid occurs
- Strain space multiple mechanism model (Iai, et al 1992, Iai 1993): 3D constitutive law that is expressed as a superposition of 300 of 1D springs
- Computation can be unstable, but it is overcome with a stabilization method (Kusakabe et al. 2021)



Governing Equation
Motion equation of soil

$$\rho \frac{\partial^2 \boldsymbol{u}}{\partial t} - \frac{\partial \boldsymbol{\sigma}}{\partial \boldsymbol{x}} = \boldsymbol{f}$$

discretized with FEM and Newmark β method

⇩

Sparse matrix equation with 1 million – 1 billion DOFs

$$\boldsymbol{A}\delta\boldsymbol{u} = \boldsymbol{b}$$

solved over 10 K time steps using conjugate gradient (CG)-based method ($\boldsymbol{A}$ is updated every time step)

GPU-accelerated Simulation

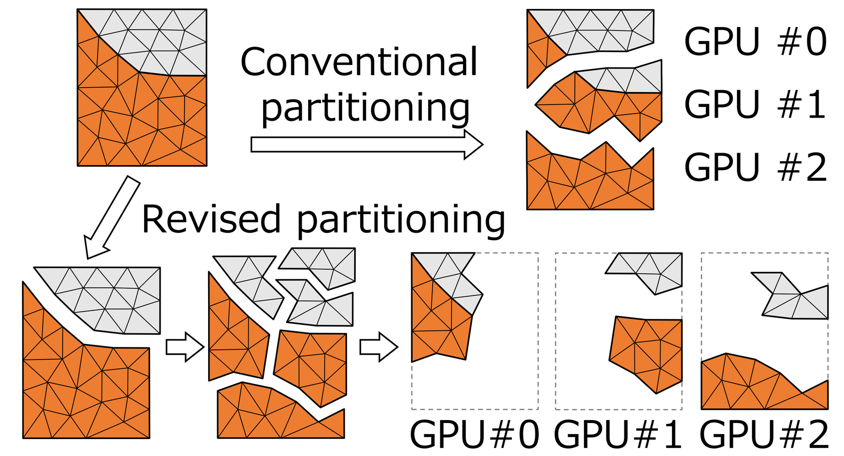
CG-based method to solve the equation
- Adaptive CG method is used
- In preconditioner, preconditioning equation $\boldsymbol{Az} = \boldsymbol{r}$ is solved with the preconditioned CG method
- Multigrid method and mixed precision are used in preconditioner to reduce computational cost without compromising the solution accuracy
- Whole simulation is parallelized with MPI and OpenACC

$\delta\boldsymbol{u} \Leftarrow \delta\boldsymbol{u}_0, \boldsymbol{r} \Leftarrow \boldsymbol{b} - \boldsymbol{A}\delta\boldsymbol{u}$
do while $(\|\boldsymbol{r}\|/\|\boldsymbol{b}\| < \varepsilon_{\mathrm{tol}})$
  Solve $\boldsymbol{Az} = \boldsymbol{r}$
  use $\boldsymbol{z}$ to update $\delta\boldsymbol{u}$
  $\boldsymbol{r} \Leftarrow \boldsymbol{b} - \boldsymbol{A}\delta\boldsymbol{u}$
end while
[In double precision]

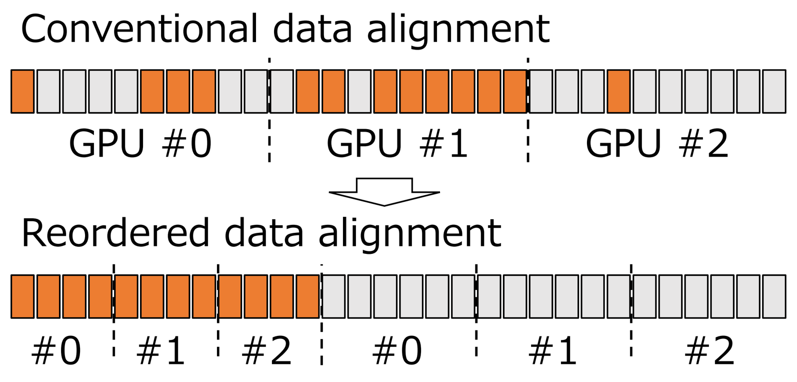
Preconditioner
- Solve $\boldsymbol{Az} = \boldsymbol{r}$ with PCG on a coarse mesh
- ↓ Use as initial solution
- Solve $\boldsymbol{Az} = \boldsymbol{r}$ with PCG on the original mesh

[In single precision]

Load Balancing



Revised domain partitioning



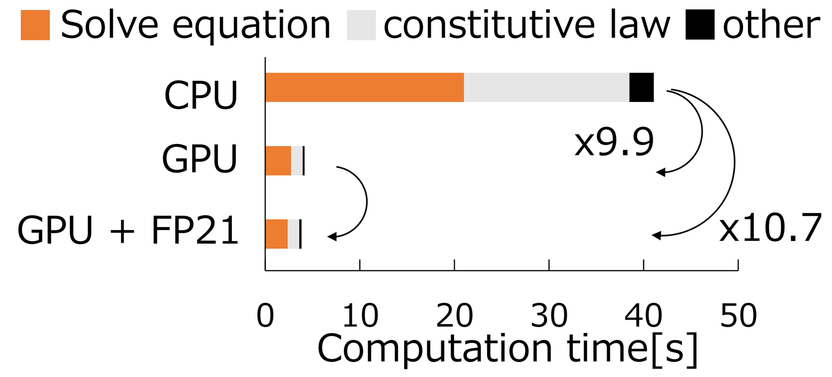
Rearrangement of elements

- Load balance is improved → high parallel efficiency
- More sequential memory access → suitable for GPU computing

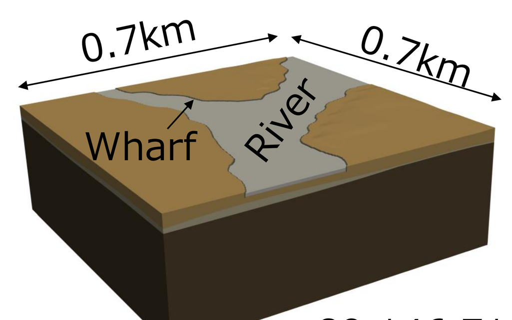
MPI communication with a 21-bit data type
- Computation is accelerated by GPU; communication is not
  → Communication can be a bottleneck
- FP21 variables are used in MPI communication in preconditioner
- 3 x FP21 variables (63 bits) are packed to a double precision variable (64 bits) and communicated among GPUs

	sign	exponent	fraction
Single precision (32 bits)	1 bit	8 bits	23 bits
FP21 (21 bits)	1 bit	8 bits	12 bits

Performance measurement
- Comparison on a compute node on AI Bridging Cloud Infrastructure [2] (ABCI)
  - 4,854,570 DOFs, 100 time steps
  - 2 CPUs (Intel Xeon Gold 6148)
  - 4 GPUs (NVIDIA Tesla V100 SXM2)
  - 10.7-fold speedup by using GPUs



- Comparison of large-scale simulation



89,146,716 DOFs
30,000 time steps

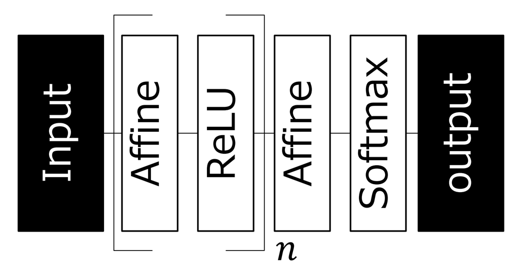
Oakforest-PACS
128 computing nodes × 14 h 37 min
(1 Intel Xeon Phi 7250 CPU/node)
⇩
ABCI
13 computing nodes × 3 h 33 min
(4 NVIDIA Tesla V100 SXM2 GPUs/node)

Without high performance computing: 282K DOFs × 40K time steps → 1 CPU × 1 month

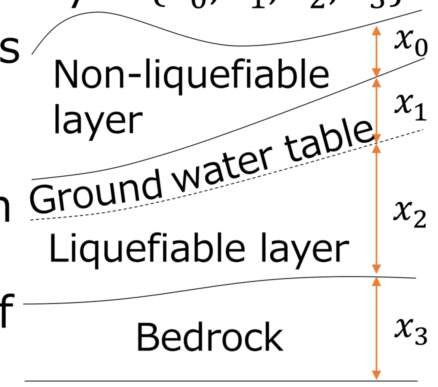
Developed method enables faster simulation with smaller computation environment

Neural Network based surrogate model

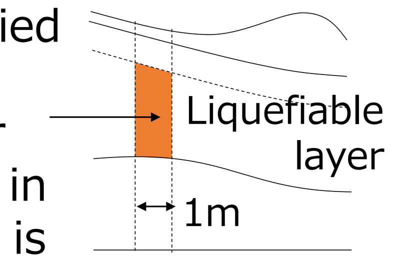
- Utilizing domain specific knowledge, a surrogate model of complex soil liquefaction simulation was successfully constructed with relatively a small neural network
- Training data were generated such that its statistical information is similar to that of the target soil model, leading to efficient training with a relatively small number of training data



Input: thickness of each layer $\{x_0, x_1, x_2, x_3\}$
- Sampled at 1 m intervals
- Based on earthquake engineering knowledge that thickness and depth of liquefiable layer have influence on likelihood of soil liquefaction

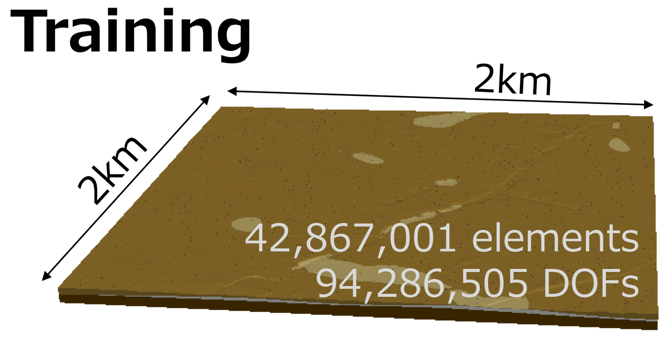


Output: whether soil gets liquefied
- Judge to be liquefied when the max. of excess pore water pressure ratio (*) in the orange region is larger than 0.9



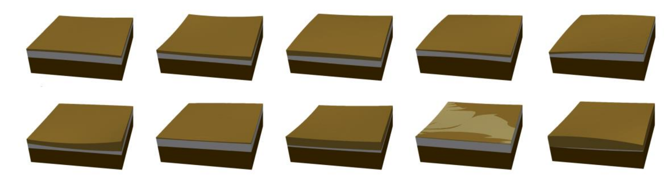
(*): an index of soil liquefaction
0: not liquefied; 1: completely liquefied

Training



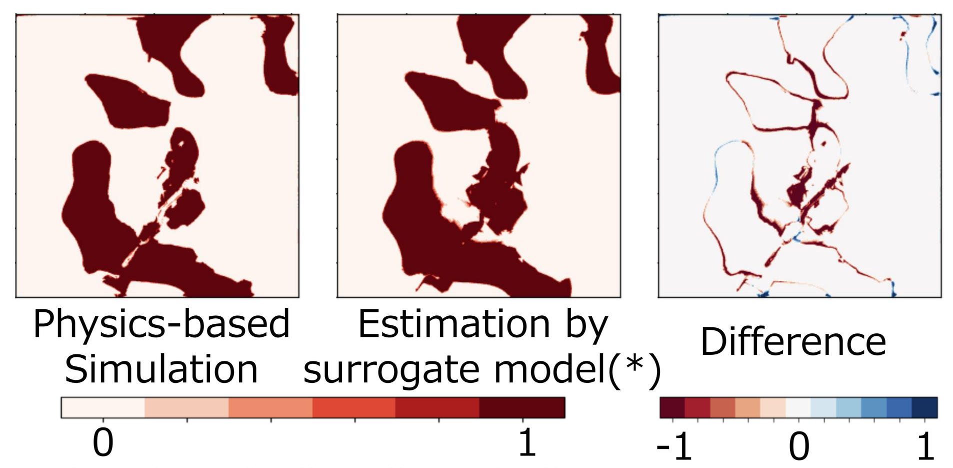
Target soil model

Latin hypercube sampling of layer depth ⇨
90% reduction in computational cost of simulation


10 models, 200m×200m×~60m
0.4 million elements, 1 million DOFs
Soil models for training NN

- Loss function: cross entropy loss
- Number of epochs: 50
- Optimizer: Adam ($\beta_1 = 0.9, \beta_2 = 0.999$, learning rate $= 10^{-4}$)

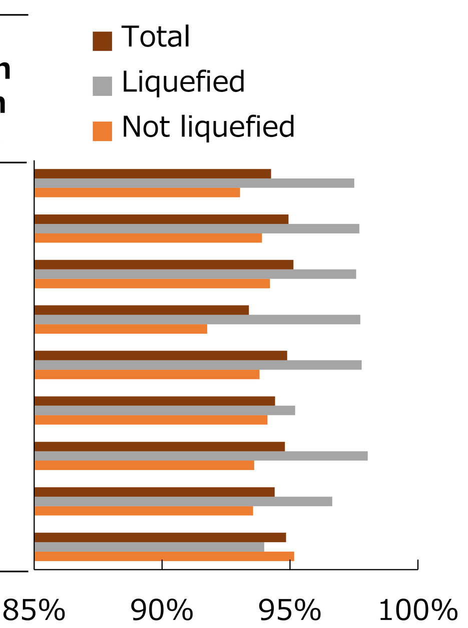
Estimation results
- Accuracy of more than 90%



Physics-based Simulation | Estimation by surrogate model(*) | Difference

(*) # of hidden layers = 4, # of units in hidden layers = 5

# of hidden layers	# of units in hidden layers
2	5
2	10
2	20
3	5
3	10
3	20
4	5
4	10
4	20



Accuracy for target soil model

Conclusion
- This poster presents an example method to realize HQC on complex nonlinear problems by efficiently combining capability and capacity computing and NN
- With GPU-accelerated Multiphysics-based simulation and surrogate models constructed from its results, it is expected that more advanced evaluation of earthquake response can be performed with smaller computation cost and time

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References

[1] Ryota Kusakabe, Kohei Fujita, Tsuyoshi Ichimura, Takuma Yamaguchi, Muneo Hori, and Lalith Wijerathne. 2021. Development of regional simulation of seismic ground-motion and induced liquefaction enhanced by GPU computing. Earthquake Engineering and Structural Dynamics 50 (2021), 197–213.
[2] National Institute of Advanced Industrial Science and Technology. 2021. About ABCI. https://abci.ai/en/about_abci/