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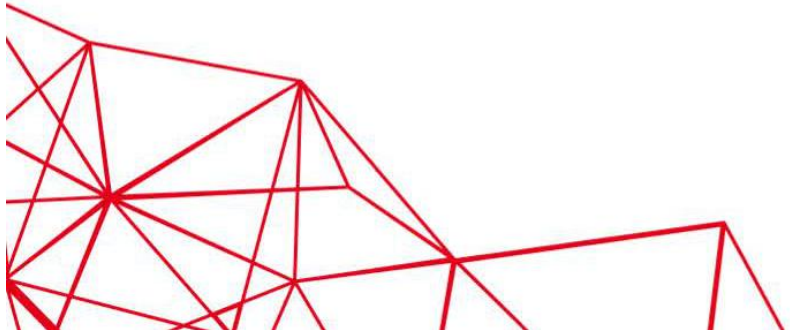

PREDICTION OF ACOUSTIC FIELDS USING A LATTICE-BOLTZMANN METHOD AND DEEP LEARNING

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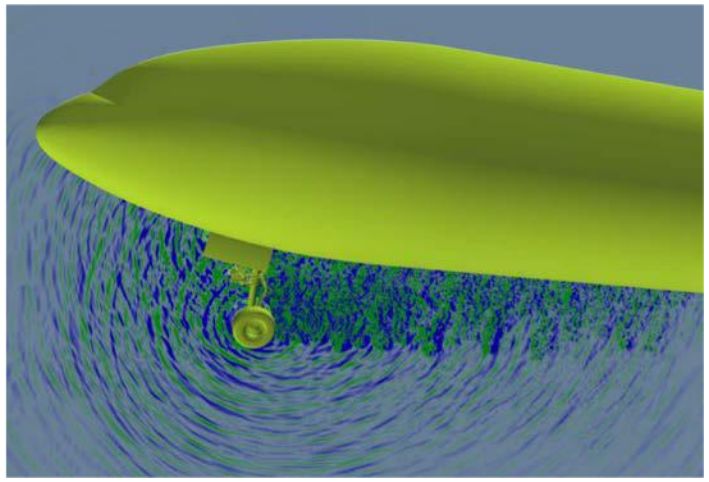
PREDICTION OF ACOUSTIC FIELDS USING A LATTICE-BOLTZMANN METHOD AND DEEP LEARNING

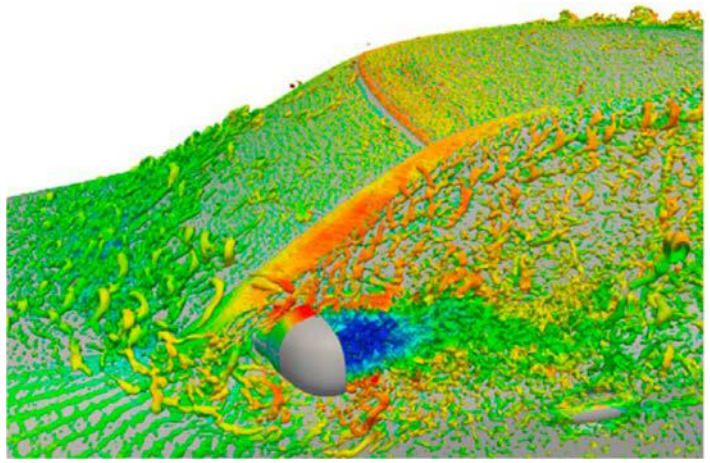
1. Introduction/Motivation
2. Numerical methods
3. Simulations
4. Machine learning techniques
5. Results
6. Summary/Outlook
7. References

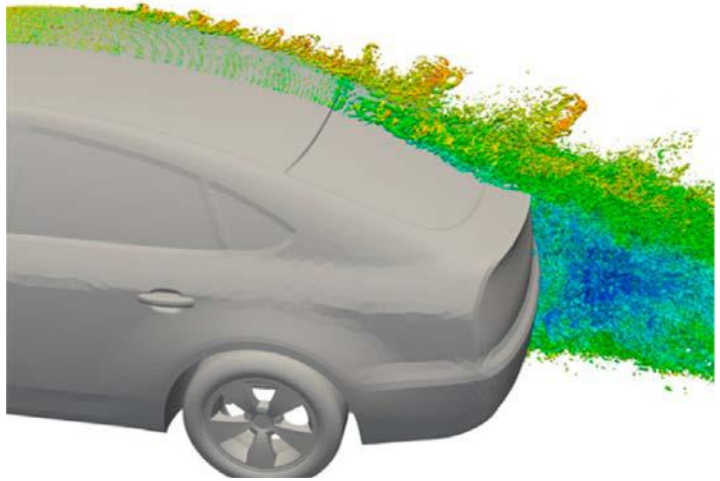
INTRODUCTION/MOTIVATION

- In many engineering applications noise sources are crucial parts of the design process
- Modeling flow-induced sound requires high-resolution numerical simulations



Aircraft undercarriage[8]



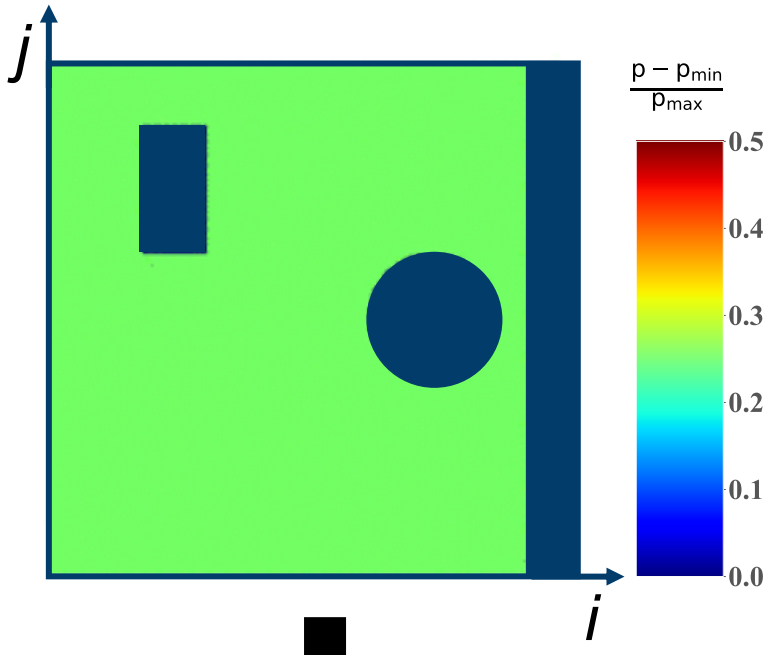


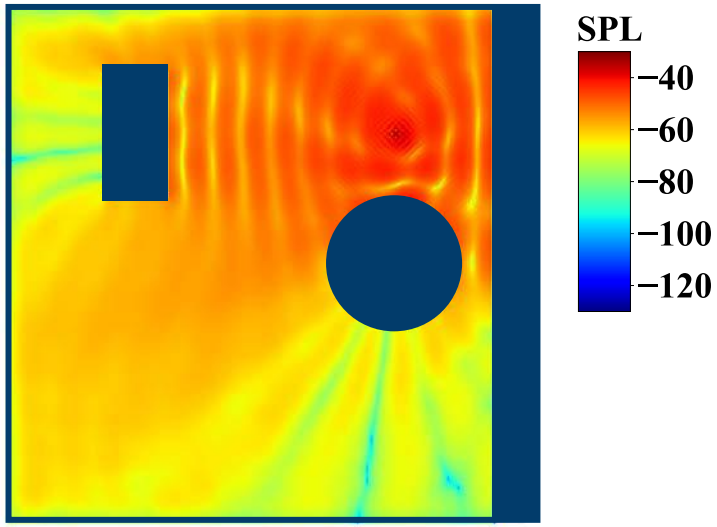
Side mirrors and rear end of vehicles[9]

- High computational costs and post-processing efforts for multiple simulations

INTRODUCTION/MOTIVATION

Acoustics fields are generated by pressure fluctuations in a domain





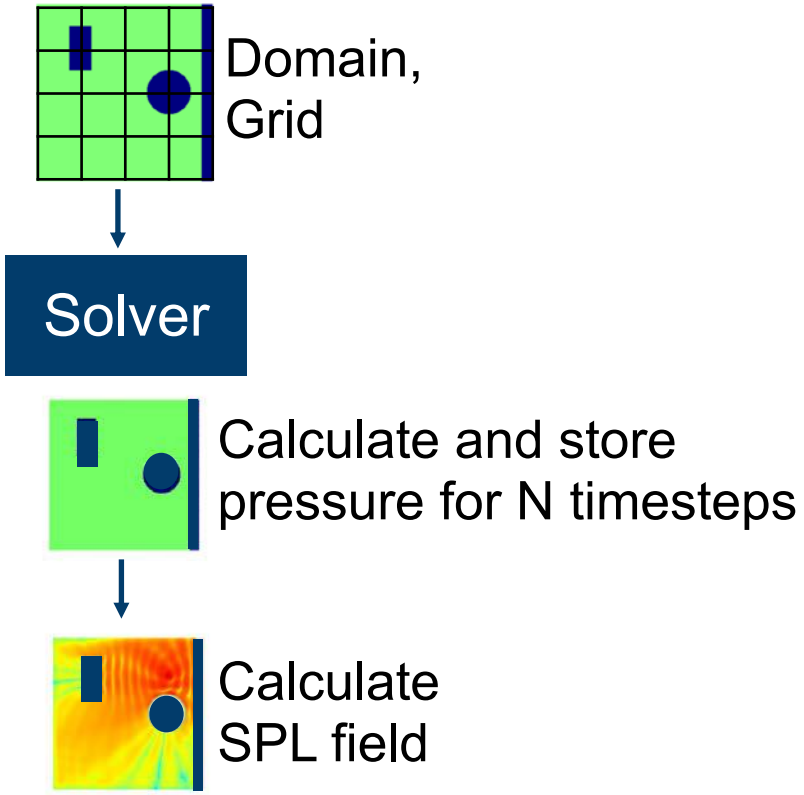
$$p'_{rms}(i,j) = \sqrt{\frac{\sum_{n=1}^{N}\left(p_n(i,j) - p_{avg}(i,j)\right)^2}{N}}$$

$$SPL(i,j) = 20\log_{10}(p'_{rms}(i,j))$$

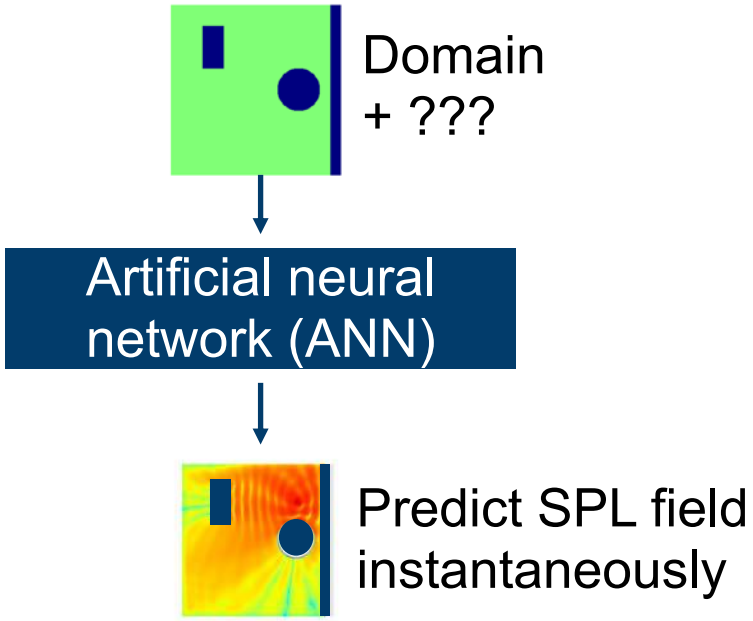
INTRODUCTION

Two established methods of predicting acoustics fields:

1. Numerical simulation



2. Surrogate model



NUMERICAL METHODS

Lattice-Boltzmann method:

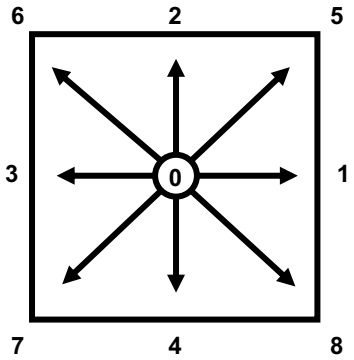
- f (x,ξ,t) is the *Particle Probability Distribution Function* (PPDF)
  (position: x, particle velocity ξ, time t)

- LBM-BGK model[1]: $\frac{\partial f}{\partial t} + \xi_i \frac{\partial f}{\partial x_i} = -\frac{1}{\tau}(f - f^{eq})$

  Relaxation until fluid reaches equilibrium state after collision with other fluid particles

  Evolution of fluid

- Discretization: D2Q9 model, 8 directions (i), i=0: particles stay in cell



$$f_i(\boldsymbol{x} + \xi_i \Delta t, t + \Delta t) = f_i(\boldsymbol{x}, t) - \frac{1}{\tau}[f_i(\boldsymbol{x}, t) - f_i^{eq}(\boldsymbol{x}, t)]$$

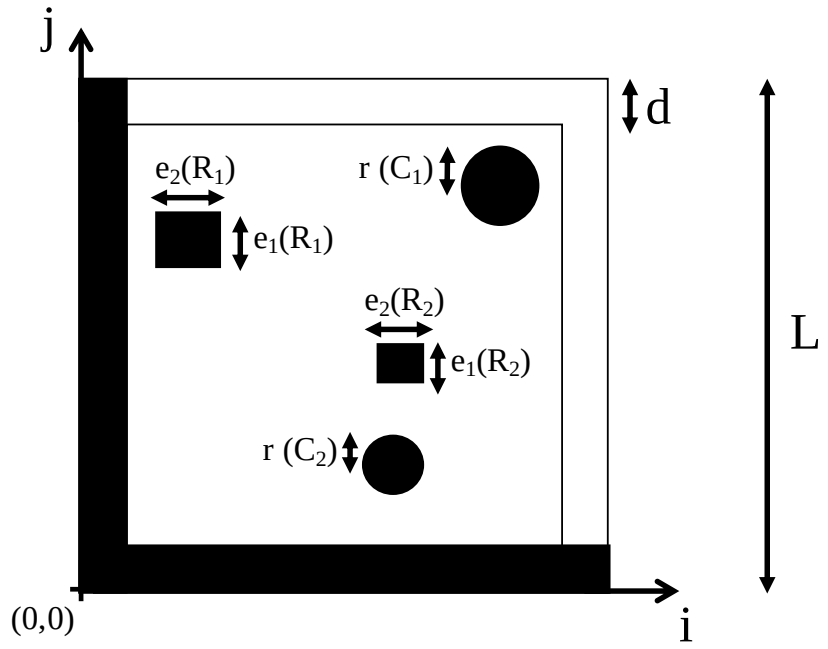
$f_i(\boldsymbol{x}, t)$ is known from previous time step
$f_i^{eq}(\boldsymbol{x}, t)$ is known from gas dynamics[2]

Get macroscopic quantities, e.g. density: $\rho = \sum_i f_i$
Get pressure from ideal gas law: $p = c_s^2 \rho$

NUMERICAL METHODS

Geometrical setup for generating training data:

- 2D square domain (length: L)
- Randomly distributed rectangular (R) and circular (C) objects
- Random edge size (e) and radius (r)
- Objects have minimum distance (d) from domain boundary
- Objects may overlap



- Monopoles located in the domain cause oscillations in density: *S(t)*

$$S(t) = \rho_\infty \sin(2\pi\omega t)$$

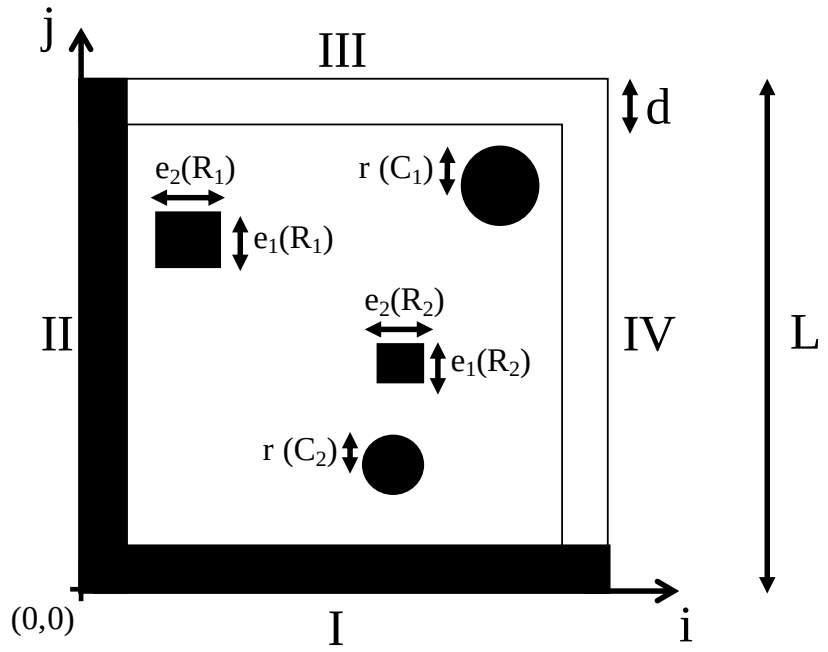
Amplitude: ρ_∞
Frequency: ω

NUMERICAL METHODS

Two types of boundary conditions:

1. Wall boundary condition (WBC):
   - No-slip behaviour (boundaries I and II)
   - PPDFs are reflectively bounced back

2. Non-reflecting boundary condition (NRBC)[3]
   - Buffer layer (boundaries III and IV)
   - Complete dissipation of acoustic waves



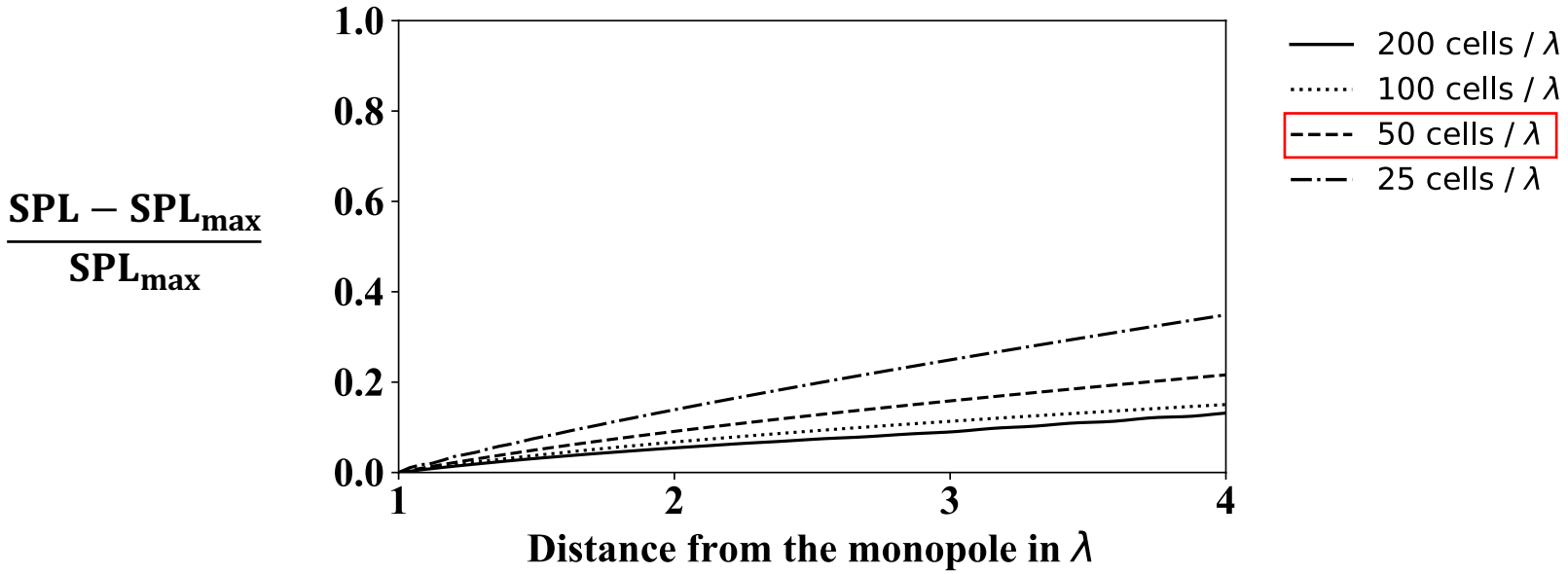
$$f_i(\boldsymbol{x} + \xi_i \Delta t, t + \Delta t) = f_i(\boldsymbol{x}, t) - \frac{1}{\tau}\left[f_i(\boldsymbol{x}, t) - f_i^{eq}(\boldsymbol{x}, t)\right] - \sigma(f_i^{eq}(x, t) - f_a)$$

$$\sigma = \sigma_m \left(\frac{\tilde{\delta}}{d}\right)^2$$

Distance to beginning of buffer layer: $\tilde{\delta}$
Weighting factor: σ_m

SIMULATIONS

- Simulation properties:
  - Up to 20,000 simulations (2 min./simulation on an NVIDIA K80 GPU)
  - 3,000 time steps per simulation (RMS period: 1,000-3,000)
  - Monopoles have a fixed frequency and amplitude
- Grid refinement study: cells per wavelength (λ)



MACHINE LEARNING TECHNIQUES

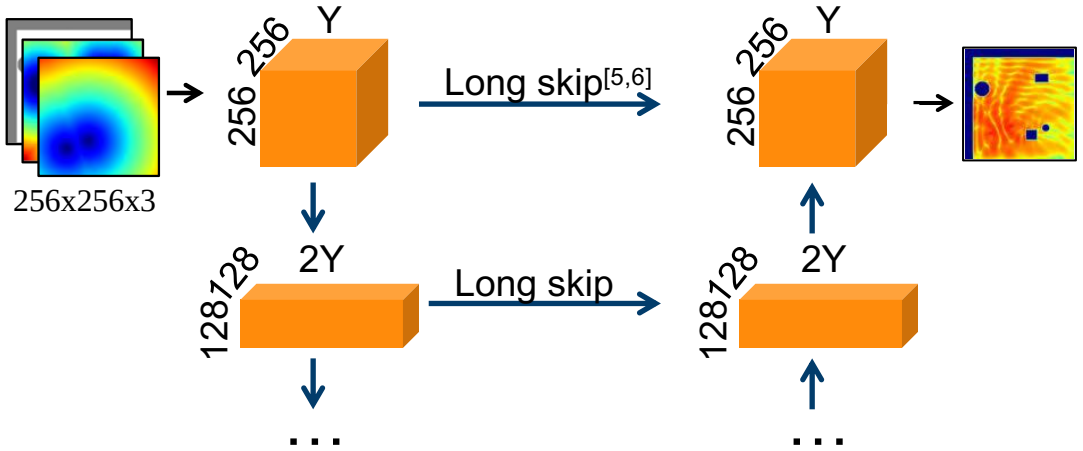
- Input/Output:

  Locations and types of bc

  Distances[4] to objects

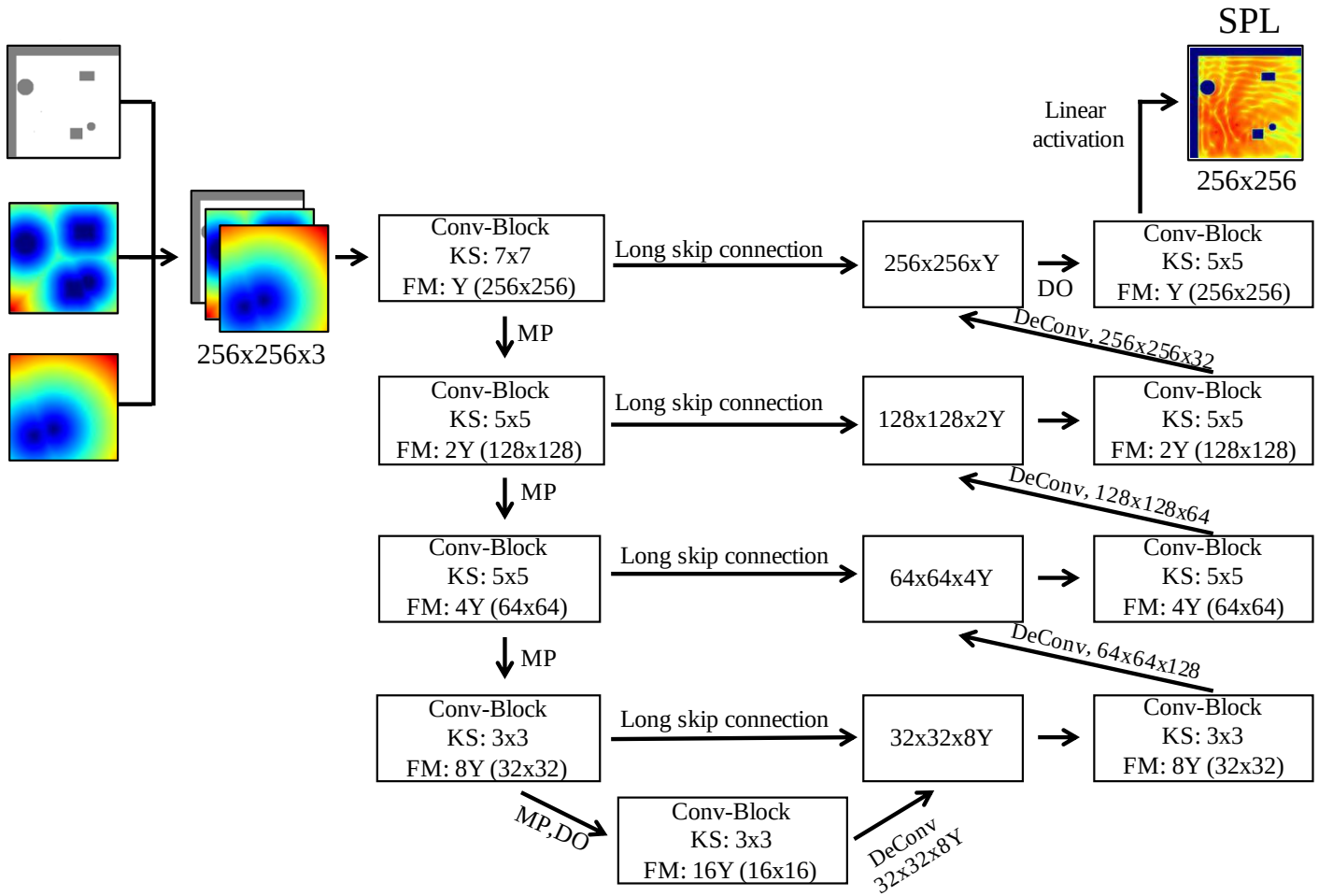
  Distances to monopoles

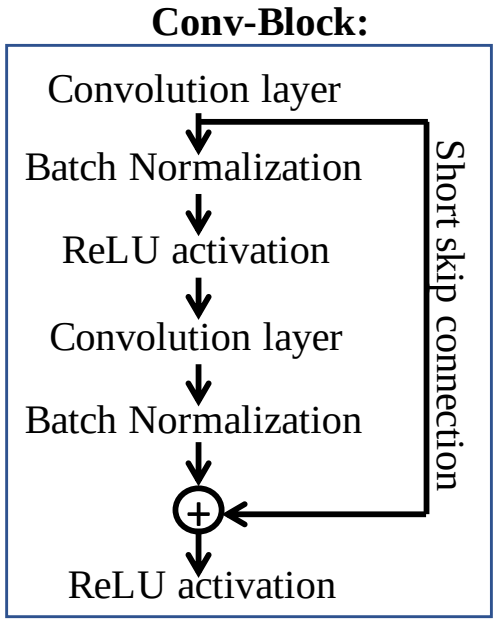
- Network architecture: CNN of encoder-decoder type



MACHINE LEARNING TECHNIQUES

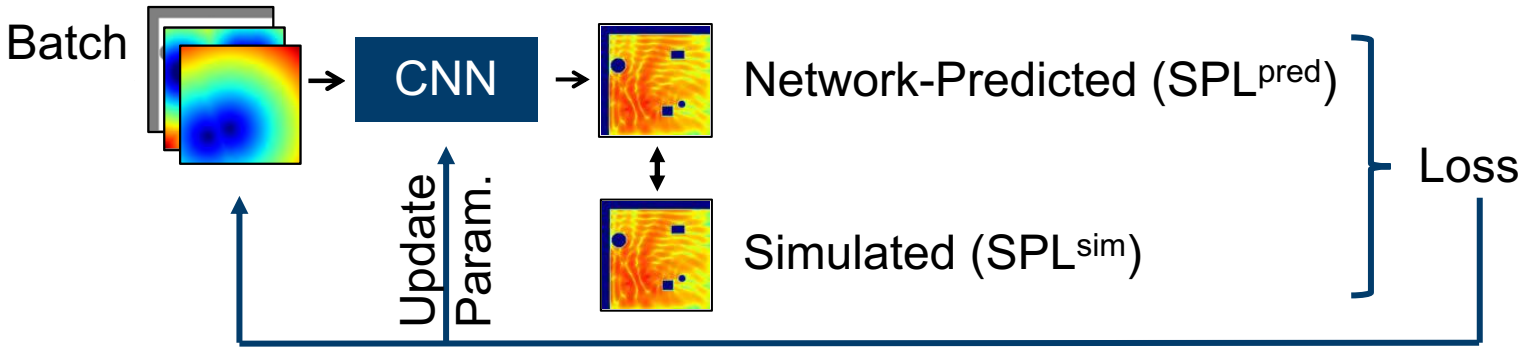
Network architecture:





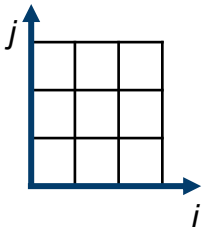
MACHINE LEARNING TECHNIQUES

- Supervised learning:



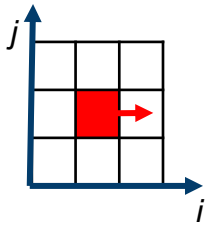
- Loss function = L_{MSE} + L_{GDL}

$$L_{MSE} = \frac{1}{m^2}\sum_{i=1}^{m}\sum_{j=1}^{m}\left(SPL(i,j)^{sim} - SPL(i,j)^{pred}\right)^2$$



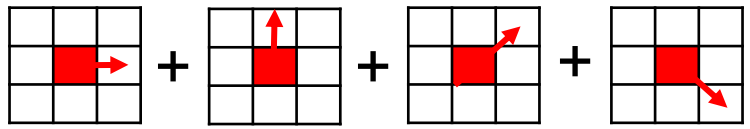
$$i, j \in 1, \ldots, m$$

L_{GDL}: Gradient loss[7]



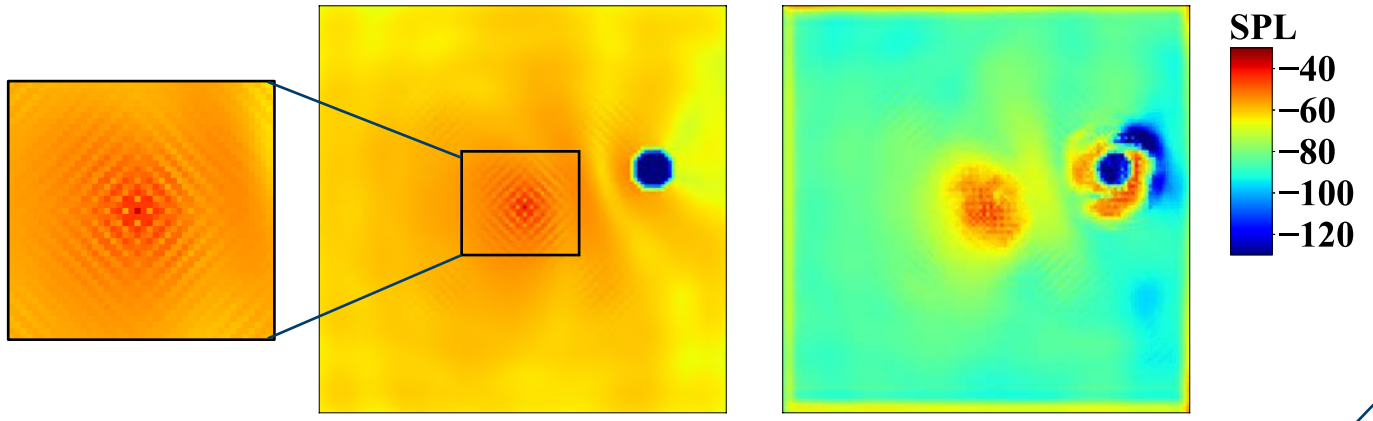
$$\frac{\partial\, SPL}{\partial i} = \frac{SPL(i+1) - SPL(i)}{\Delta i} + \sigma(\Delta i)$$

1st-order accurate forward difference



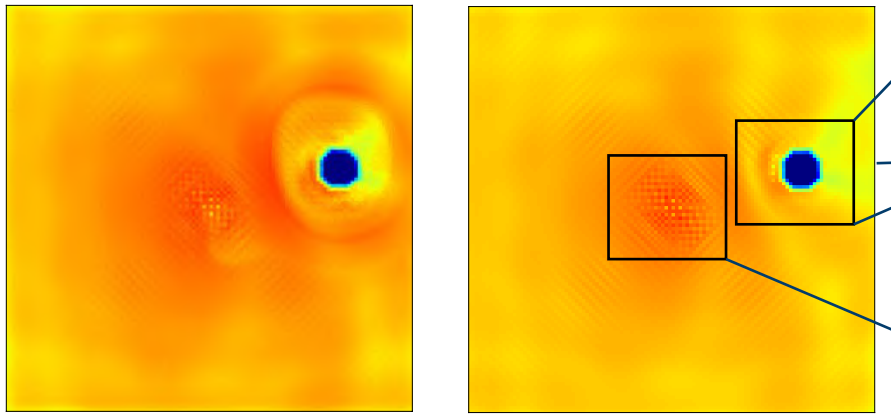
RESULTS

Investigating the number of feature maps (Y):



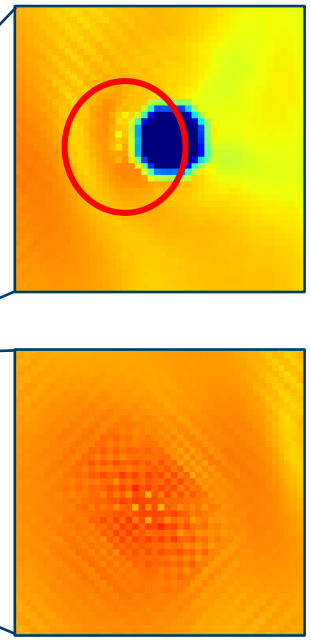
Simulation (128x128)

Y=8 (517,867 par.)



Y=16 (2,066,001 par.)

Y=32 (8,253,089 par.)

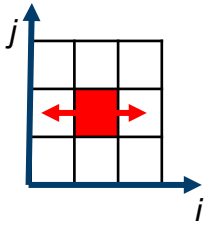


Unphysical predictions near object surface and monopoles

RESULTS

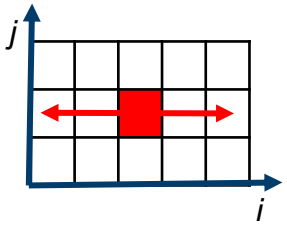
- Investigating the loss function:
  - Monopoles are point sources
  - Waves spread into all directions

- L_{GDL}: Change from Forward Difference to Central Difference
  - 2nd-order accurate:



$$\frac{\partial\, SPL}{\partial i} = \frac{SPL(i+1) - SPL(i-1)}{2(\Delta i)} + \mathcal{O}(\Delta i)^2$$

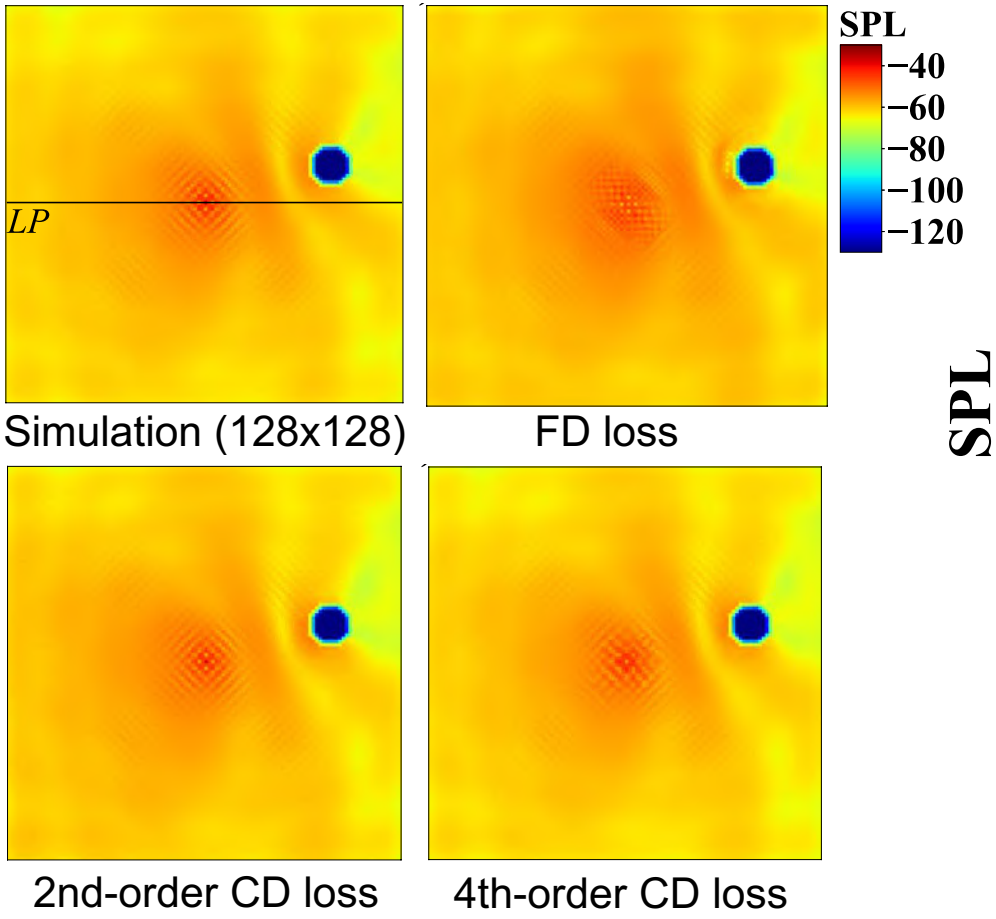
  - 4th-order accurate:

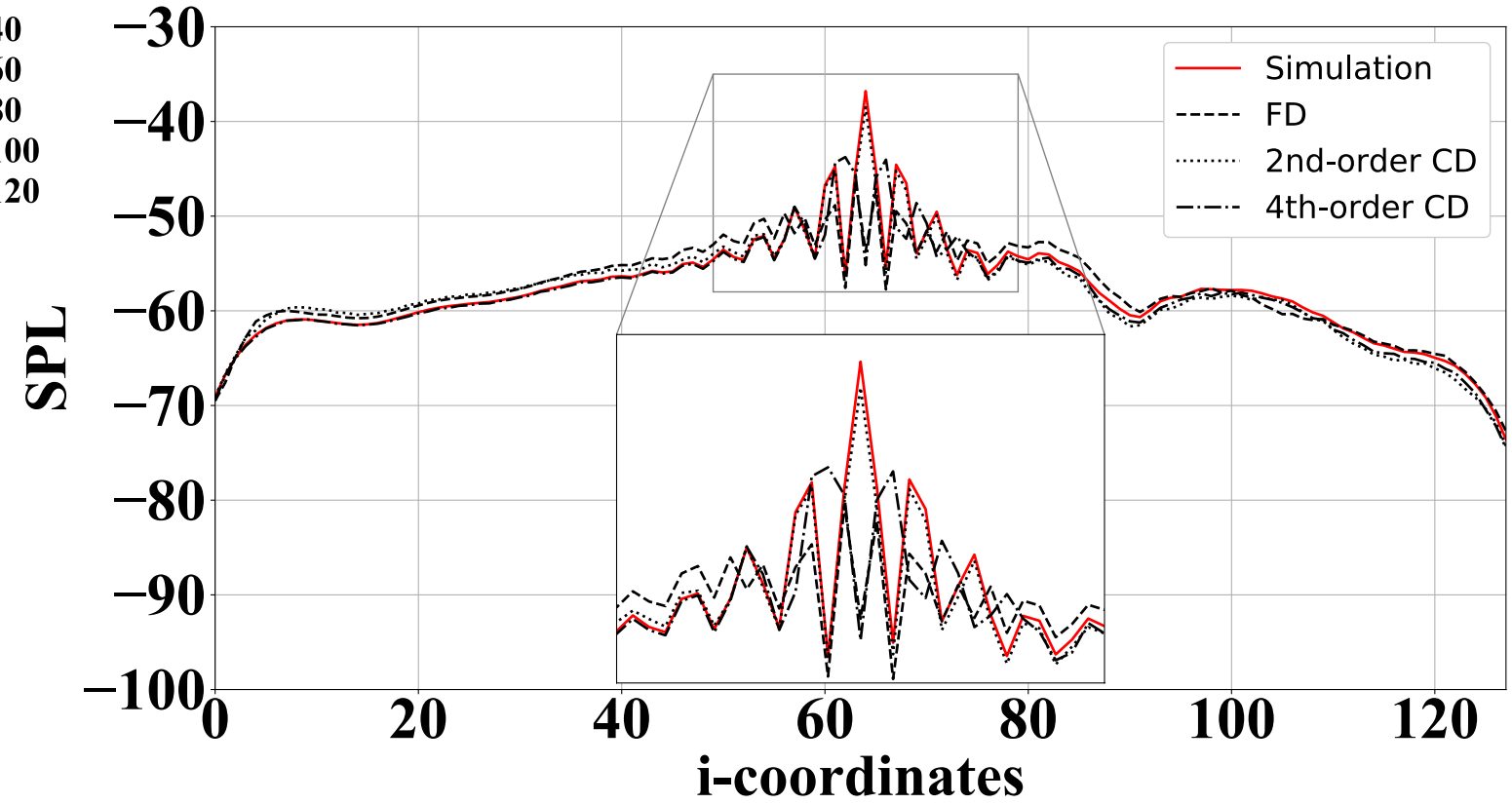


$$\frac{\partial\, SPL}{\partial i} = \frac{-SPL(i+2) + 8\,SPL(i+1) - 8\,SPL(i-1) + SPL(i-2)}{12(\Delta i)} + \mathcal{O}(\Delta i)^4$$

RESULTS

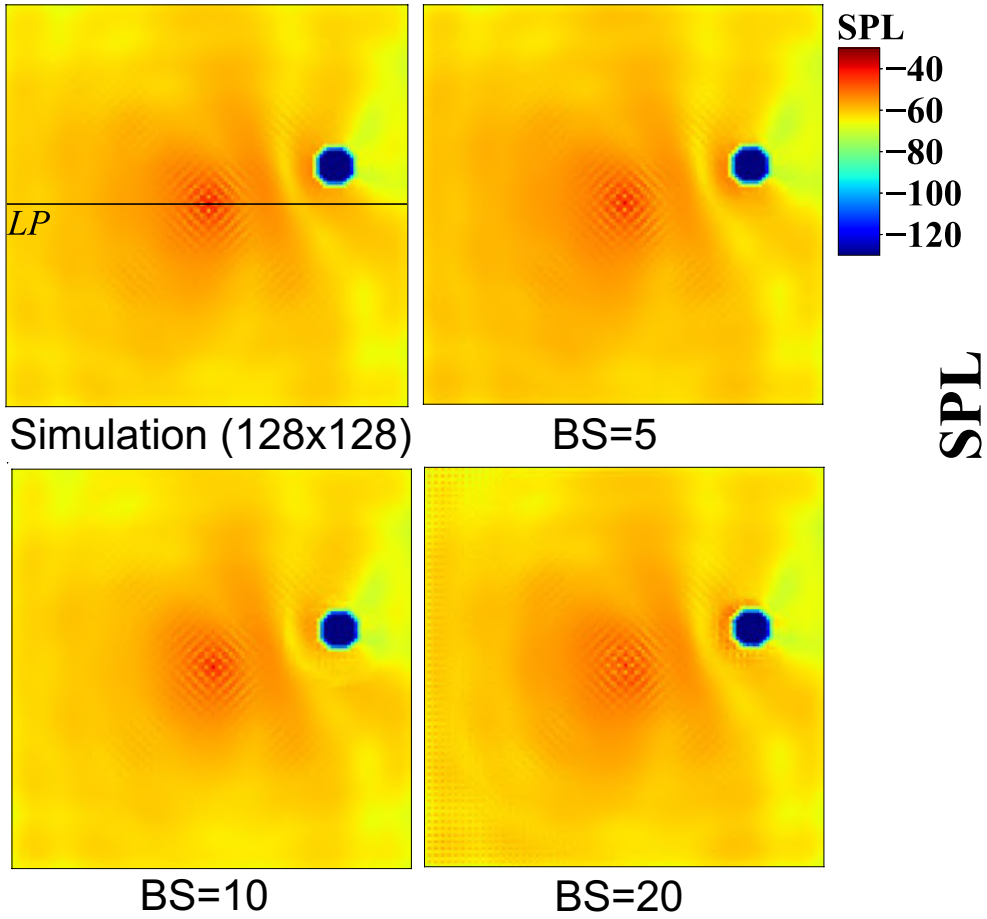
Investigating the loss function:

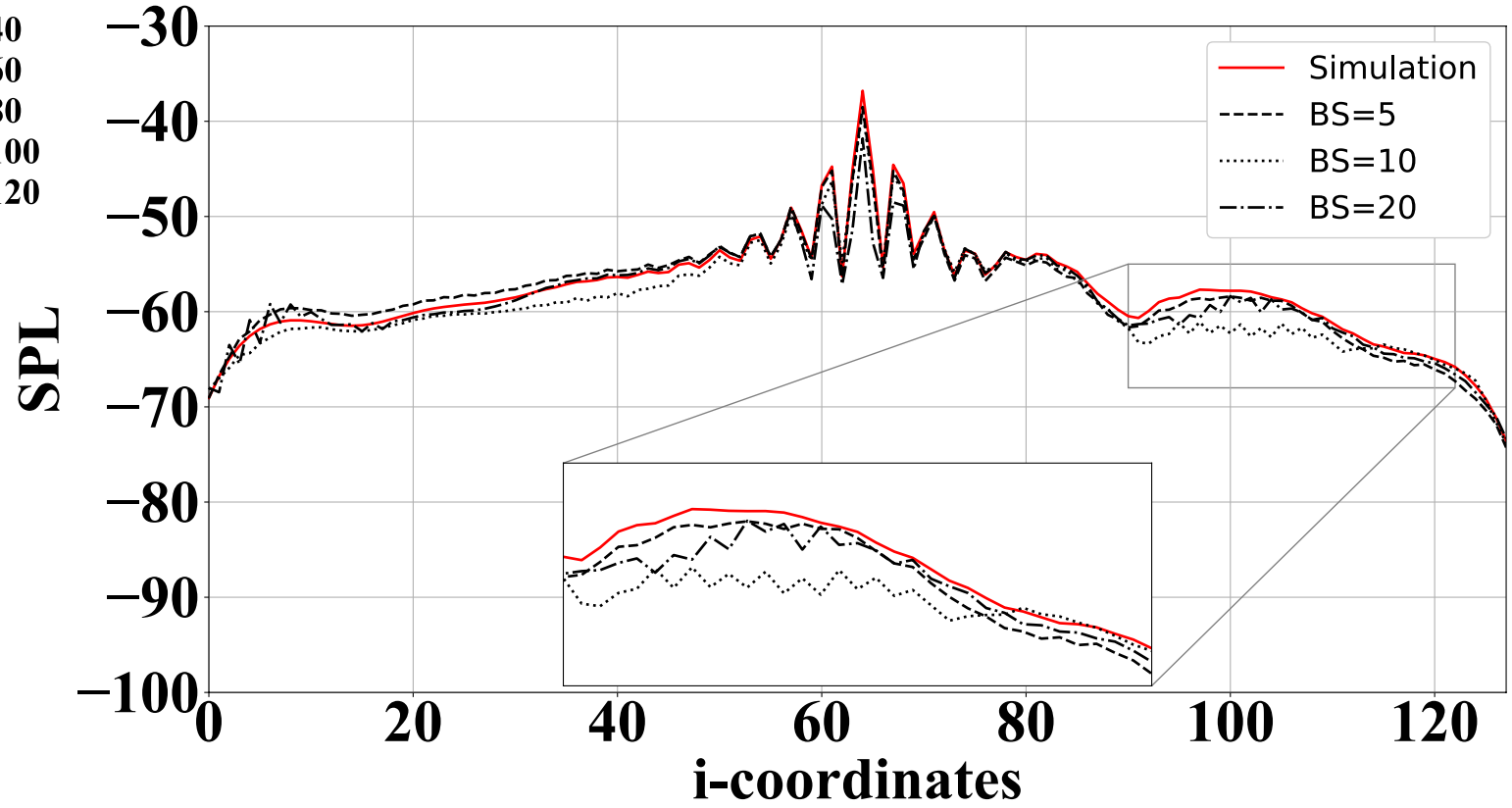




RESULTS

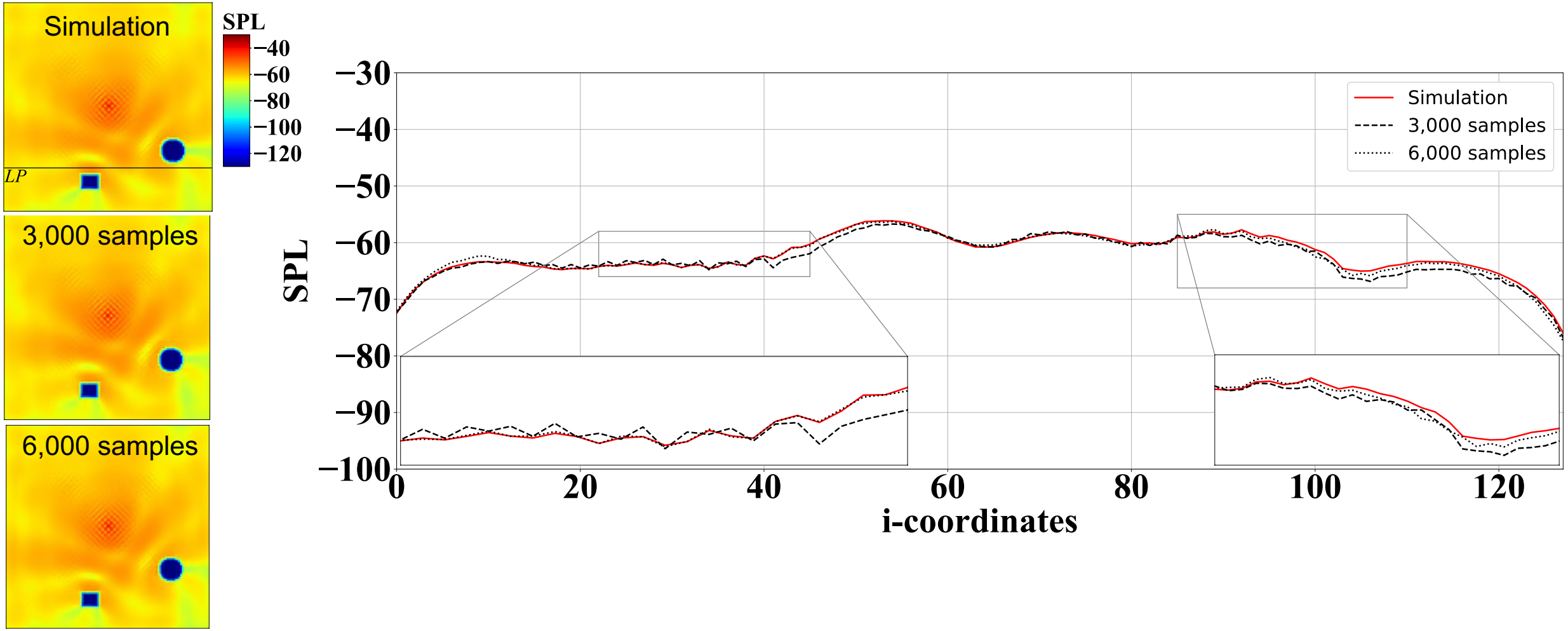
Investigating the batch size (BS):





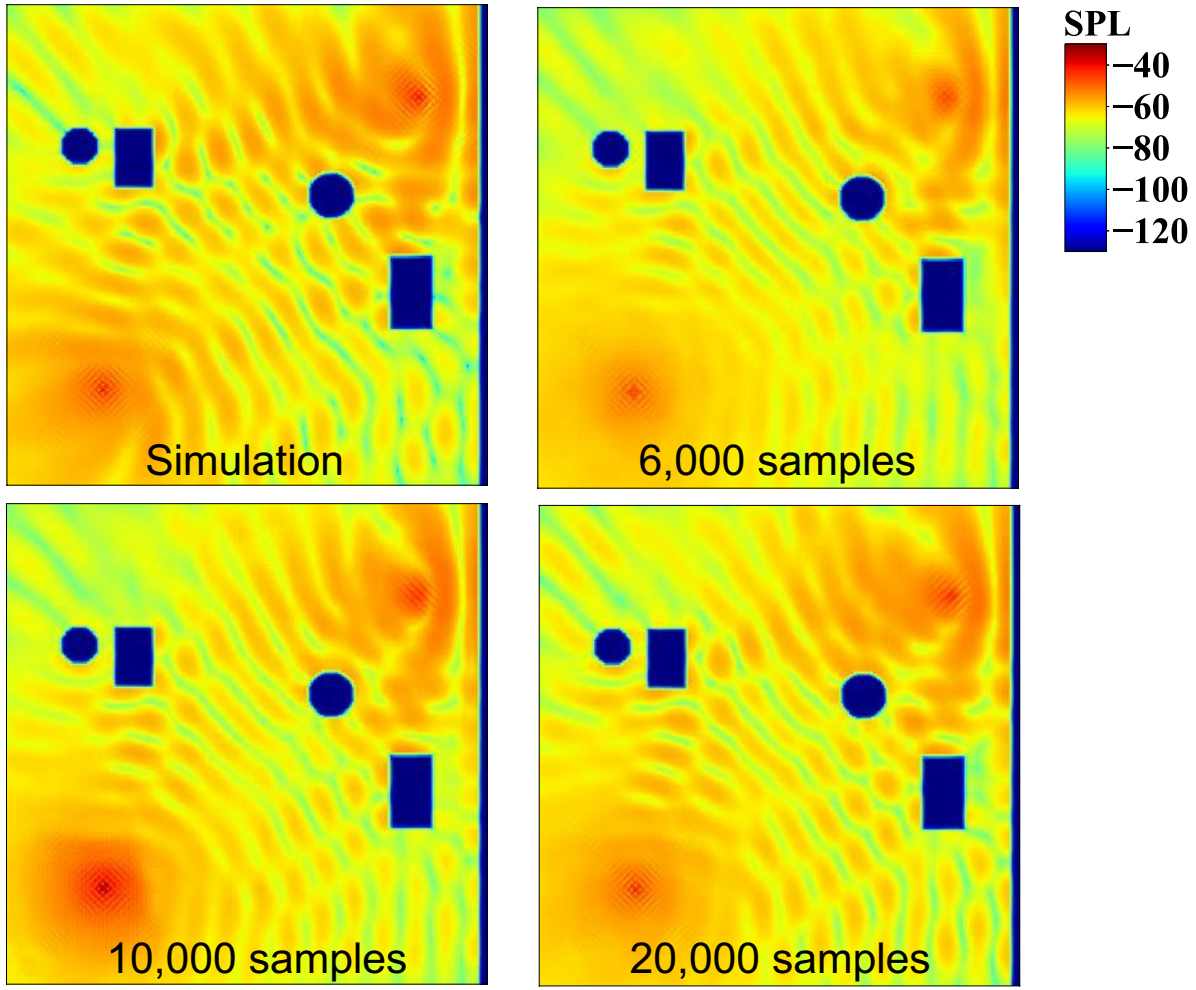
RESULTS

Investigating the number of training data:



RESULTS

Case with 2 Monopoles, 4 Objects, 256x256 cells:



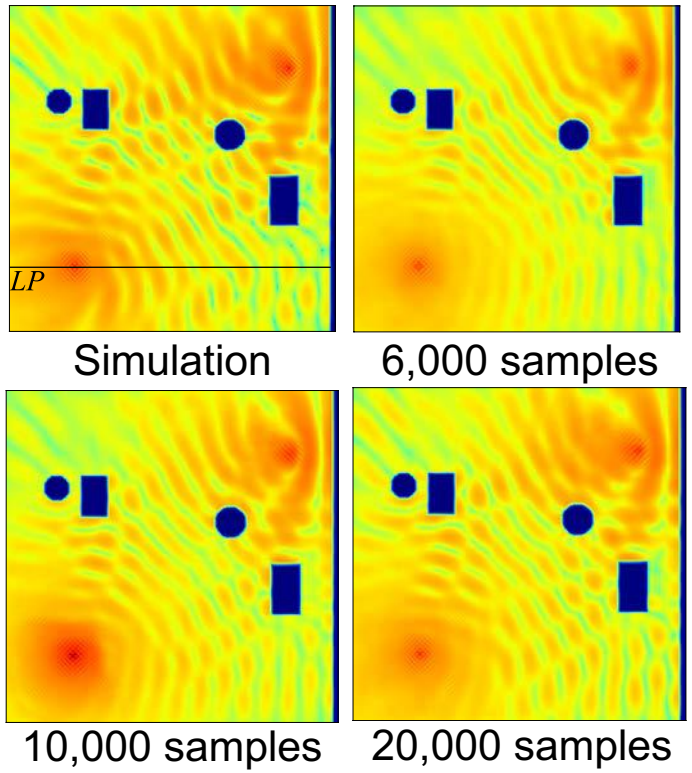
Average error:

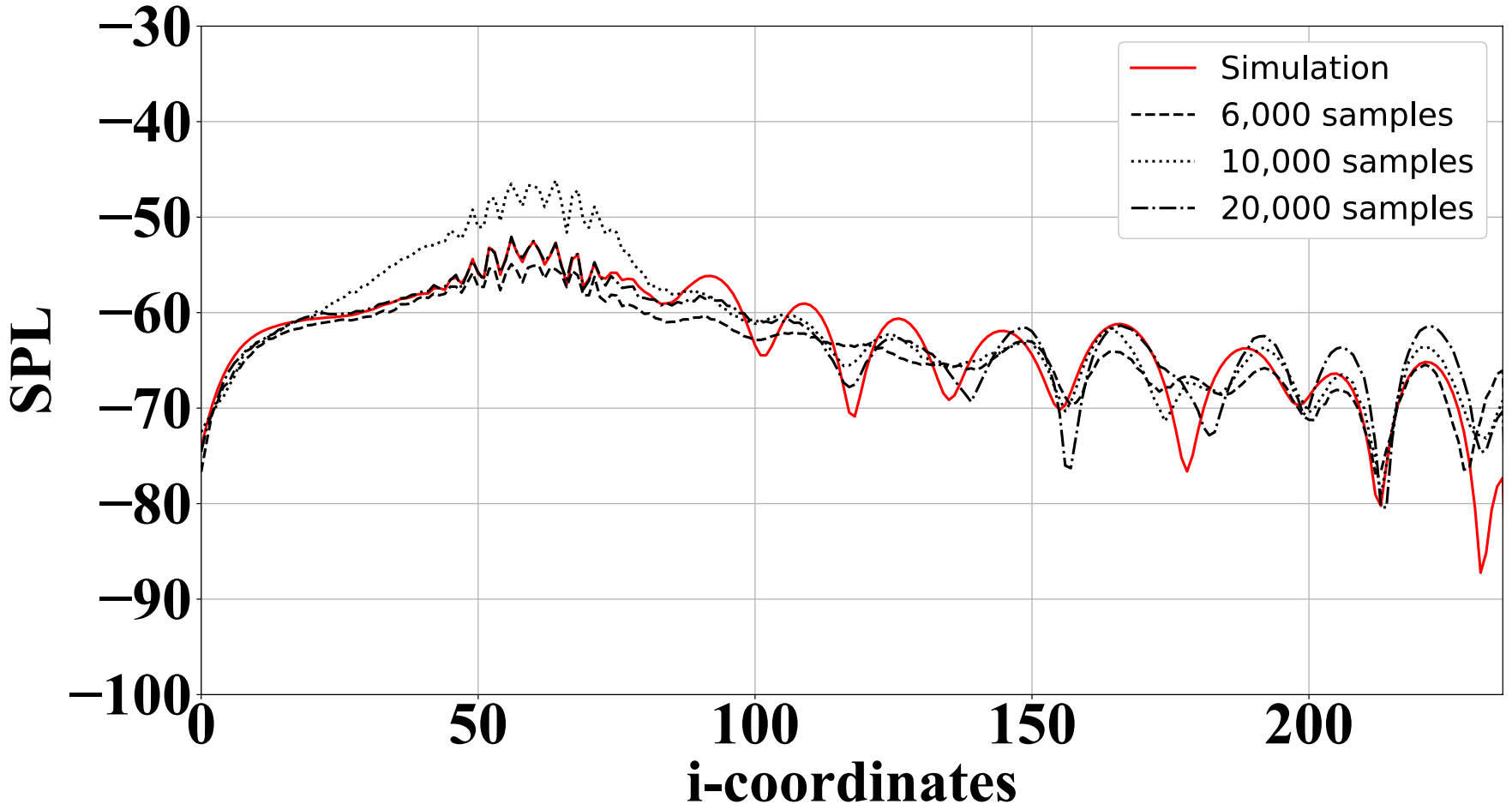
$$E = \frac{1}{m^2} \sum_{i=1}^{m} \sum_{j=1}^{m} \frac{\left| SPL^{pred}(i,j) - SPL^{sim}(i,j) \right|}{\left| SPL^{sim}_{max} - SPL^{sim}_{min} \right|}$$

Training data	Average error (E)
6,000	0.02581
10,000	0.02268
20,000	0.01937

RESULTS

Case with 2 Monopoles, 4 Objects, 256x256 cells:



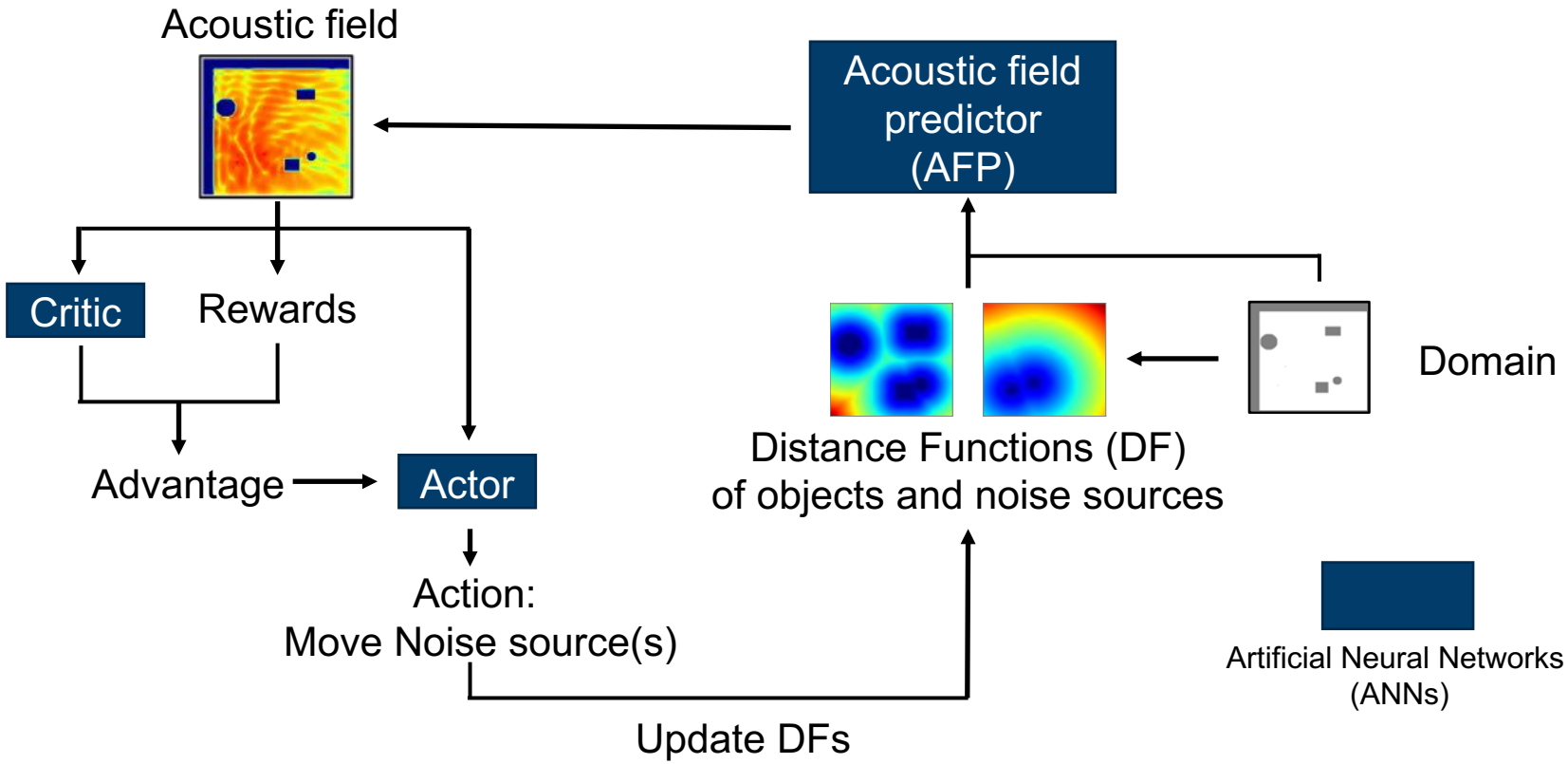


SUMMARY/OUTLOOK

- Artificial Neural Networks have been used as surrogate models to predict acoustic fields
- Training data have been generated with a Lattice-Boltzmann method
- The following topics are investigated at present:
  - 2D domain → 3D domain
  - Various amplitudes and frequencies
  - Increase level of generalization
  - Adversarial training

SUMMARY/OUTLOOK

- Why are we doing this?
  Plan: Position Optimization of Noise Sources with Reinforcement Learning



CONTACT/REFERENCES

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