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

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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\textsuperscript{[8]}

Side mirrors and rear end of vehicles\textsuperscript{[9]}

• High computational costs and post-processing efforts for multiple simulations
Acoustics fields are generated by pressure fluctuations in a domain.

\[ p_{\text{rms}}(i,j) = \sqrt{\frac{\sum_{n=1}^{N} (p_n(i,j) - p_{\text{avg}}(i,j))^2}{N}} \]

\[ SPL(i,j) = 20 \log_{10}(p_{\text{rms}}(i,j)) \]
INTRODUCTION

Two established methods of predicting acoustics fields:

1. Numerical simulation
   - Domain, Grid
   - Solver
   - Calculate and store pressure for N timesteps
   - Calculate SPL field

2. Surrogate model
   - Domain + ???
   - Artificial neural network (ANN)
   - Predict SPL field instantaneously
Lattice-Boltzmann method:

- \( f(x, \xi, t) \) is the \textit{Particle Probability Distribution Function} (PPDF) (position: \( x \), particle velocity \( \xi \), time \( t \))

- \textbf{LBM-BGK model\textsuperscript{[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

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

  Evolution of fluid

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

\[
\begin{align*}
  f_i(x + \xi_i \Delta t, t + \Delta t) &= f_i(x, t) - \frac{1}{\tau} [f_i(x, t) - f_i^{eq}(x, t)] \\
  f_i(x, t) &\text{ is known from previous time step} \\
  f_i^{eq}(x, t) &\text{ is known from gas dynamics\textsuperscript{[2]}}
\end{align*}
\]

Get macroscopic quantities, e.g. density: \( \rho = \sum_i f_i \)

Get pressure from ideal gas law: \( p = c_s^2 \rho \)
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: $\rho_\infty$
Frequency: $\omega$
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

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

\[
\sigma = \sigma_m \left( \frac{\delta}{d} \right)^2
\]

Distance to beginning of buffer layer: \(\delta\)

Weighting factor: \(\sigma_m\)
• 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 ($\lambda$)
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:

\[ \text{Batch} \xrightarrow{\text{CNN}} \text{Network-Predicted (SPL}^{\text{pred}}) \]
\[ \xrightarrow{\text{Simulated (SPL}^{\text{sim}})} \text{Loss} \]

• Loss function = \( L_{\text{MSE}} + L_{\text{GDL}} \)

\[
L_{\text{MSE}} = \frac{1}{m^2} \sum_{i=1}^{m} \sum_{j=1}^{m} (\text{SPL}(i,j)^{\text{sim}} - \text{SPL}(i,j)^{\text{pred}})^2
\]

\[ j \]
\[ i \]

\( i, j \in 1, \ldots, m \)

\[ L_{\text{GDL}}: \text{Gradient loss}^{[7]} \]

\[
\frac{\partial \text{SPL}}{\partial i} = \frac{\text{SPL}(i + 1) - \text{SPL}(i)}{\Delta i} + \sigma(\Delta i)
\]

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

• $L_{\text{GDL}}$: Change from Forward Difference to Central Difference
  • 2nd-order accurate:
    \[
    \frac{\partial \text{SPL}}{\partial i} = \frac{\text{SPL}(i + 1) - \text{SPL}(i - 1)}{2(\Delta i)} + \sigma (\Delta i)^2
    \]
  • 4th-order accurate:
    \[
    \frac{\partial \text{SPL}}{\partial i} = \frac{-\text{SPL}(i + 2) + 8 \text{SPL}(i + 1) - 8 \text{SPL}(i - 1) + \text{SPL}(i - 2)}{12(\Delta i)} + \sigma (\Delta i)^4
    \]
Investigating the loss function:
Investigating the batch size (BS):

RESULTS

Simulation (128x128) BS=5

Simulation (128x128) BS=10

Simulation (128x128) BS=20

SPL

i-coordinates

Simulation
BS=5
BS=10
BS=20
RESULTS

Investigating the number of training data:

- Simulation
- SPL
- 3,000 samples
- 6,000 samples

![Graph showing SPL with different sample sizes]
Case with 2 Monopoles, 4 Objects, 256x256 cells:

Average error:

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

| 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:

![Graph showing SPL over i-coordinates with simulation results at 6,000, 10,000, and 20,000 samples.]
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 $\rightarrow$ 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

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

- **Acoustic field**
  - **Critic**
    - Rewards
      - Advantage
        - Actor
          - Action: Move Noise source(s)

- **Acoustic field predictor** (AFP)
  - **Distance Functions (DF)** of objects and noise sources
    - **Domain**
      - **Update DFs**

- **Artificial Neural Networks** (ANNs)
CONTACT/REFERENCES

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