Implicit Neural Representation as a Differentiable Surrogate for Photon Propagation in a Monolithic Neutrino Detector

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Light Readout System
detection of scintillating photons at $O(\text{ns})$

$e^{-} + ^{40}\text{Ar}^{+} + ^{40}\text{Ar} \rightarrow ^{40}\text{Ar}^{*} \rightarrow 2^{40}\text{Ar} + \gamma.$

Charge Readout System
a set of Interlaced wires or pixels
drift time $O(\text{ms})$

Drift distance = Drift Velocity $\times (t - t_0)$
Examples of LArTPC Detectors

Module-0 Demonstrator
- 1st ton-scale prototype of DUNE* near detector design
- ~0.7 m x 0.7 m x 1.4 m
- divided into 2 TPCs
- pixelated charge readout
- 2 different optical detector prototypes: LCM & ArcLight

ICARUS**
- largest LArTPC in operation with wire readout
- 760 ton LAr in 2 TPCs
- each ~3.6 m x 3.9 m x 19.9 m

* DUNE: Deep Underground Neutrino Experiment
** ICARUS: Imaging Cosmic And Rare Underground Signals
Proposed LArTPC Detectors

DUNE Near Detector-Liquid Argon (ND-LAr)
- 7x5 array of 1 m x 1m x 3m detector modules (similar design as module-0 demonstrator)
- ~67 ton of LAr

DUNE Far Detector
- 4 x ~17-kton detector modules
- each ~19 m x 18 m x 66 m

*Scalability* is the key for the future
Visibility Lookup Table
- divide the detector volume into voxels of ~cm in size
- for each voxel, simulate and propagate millions of photons
- count the number of detected photons
- visibility at \((x,y,z)\) = \# detected photons / \# generated photons

- Limited by memory usage
- Not scalable for large detector
- Simulation-based, difficult to calibrate
Sinusoidal Representation Network (SIREN)

Implicit Neural Representation
Parameterize signals as continuous functions via neural networks, which are trained to map the domain the signal (e.g. spatial coordinates) to the target outputs (e.g. signal at those coordinates).

\[ f: \mathbb{R}^M \rightarrow \mathbb{R}^N \]

SIREN
a simple multilayer perceptron (MLP) network architecture along with periodic sine function activations (Sitzmann et al., arXiv:2006.09661)
Why SIREN?

By construction, SIREN is a continuous, differentiable signal representations
=> modeling signals with fine detail, AND
=> representing smooth gradient surface (and higher order of derivatives)

\[ f(x) \]

1st derivative

\[ \nabla f(x) \]

2nd derivative

SIREN (arXiv:2006.09661)

Allows wide range of applications from gradient-based algorithms, solving differential equation, optimizing on the derivative … etc
Visibility: SIREN v.s. LUT

LUT (top)
- $74 \times 77 \times 394 = 2.2$ M voxels (5 cm in size)
- 180 PMTs = ~404 M parameters

SIREN (bottom)
- 5 hidden layers, 512 hidden features
- ~1.5 M parameters

SIREN can reproduce both *values* and *gradients* of the visibility LUT with much smaller number of parameters.

Tsang et al., arXiv:2211.01505
Application of SIREN to Data Charge-to-Light Prediction

- point-like source, i.e. visibility at \((x,y,z)\), is not accessible in data
- infer light signal from physics objects (e.g. tracks)

**Light Signal**

\[ \sim \sum Q_i \cdot \text{vis}(r_i) \]

**Sum charge** \((Q_i)\) over the track image

**visibility at charge coordinates** \(r_i\)

Optimize SIREN parameters using track data

For the rest of the talk, I will show some real world applications of SIREN using cosmic rays data from *Module-0 Demonstrator*. 

**Poisson Likelihood**

\[ \mathcal{L}_{\text{track}} = \prod_{j=1}^{N} \text{Pois}(n_j | \lambda_j) \]

product of all PMTs

Observed p.e. for j-th PMT

Predicted light signal
Module-0: SIREN from Simulation

**Before Calibration**
- train SIREN with LUT from simulation (uncalibrated)
- ~10% discrepancy between observed and predicted light signals

Simulation is reasonable, but not perfect. Need \textit{calibration}.
After Calibration
- re-optimize SIREN parameters with tracks
- no bias and smaller variance

SIREN can be calibrated to remove data-simulation discrepancy.
Build a SIREN Model Directly from Data

Uncalibrated
- SIREN trained from LUT (simulation)
- suffer from data-MC discrepancy

Fine Tuning
- use uncalib. SIREN model as initial parameters
- re-optimize with tracks (calibration)

From Scratch
- random initialization of SIREN parameters
- optimize with tracks

SIREN model can be constructed from data alone, without prior knowledge from simulation.
Example Events

Only one chamber TPC-0 is presented in this study. Grayed out points (unclustered or in TPC-1) are excluded.

Better agreement after calibration.
Visibility Map (LCM)

Calibrated model gives higher visibility near SiPM.
Visibility Map (ArcLight)

Data matches simulation, with a little more diffusion in visibility.

May provide useful insights for detector R&D.
Hyper-Parameter Optimization

Optimal SIREN model for module-0 demonstrator

- determined by track data
- # of layers = 1
- # of features = 128
- ~23k parameters
- c.f. 12.6M for LUT in ~1 cm voxel size
How Many Tracks Needed?

- performance increase significantly from 5k to 50k tracks
- difference diminishes to ~0.1% from 50k and beyond
- ~100k tracks are good enough to build a SIREN model for Module-0 demonstrator
Conclusions

• propose the use of sinusoidal representation network (SIREN) to model the light propagation for LArTPCs
  • memory efficient => scalable for large detectors
  • optimizable w/ data => calibration
  • smooth gradient surface => further applications
• optimize a SIREN model using data from Module-0 demonstrator
  • fine-tuning from a simulation-based SIREN model,
  • or construct a SIREN model from data only.
• potential applications to other experiments (not limited to LArTPC)
Backup Slides
SIREN Performance

SIREN is able to represent LUT with \( \sim 1\% \) in the high visibility region (vis. \( > 1e-2 \)).

The overall (average) bias is \( \sim 7-8\% \), which is dominated by the statistical fluctuation of the LUT at low visibility.
Statistical Uncertainty in LUT

Generation of the photon library is limited by finite statistics.

The input data to the SIREN are subjected to statistical uncertainty (more prominent for voxels with low visibility).
Toy Model: A Study w/ and /o Stat. Err.

**Toy Model**: analytical (smooth) model that roughly reassemble the features of LUT. No statistical fluctuation.

**Toy Model + Noise**: sampling from toy model, assuming $1e6$ photons per voxel, ~same statistical uncertainty as the LUT.
SIREN Performance w/o Statistical Uncertainty

Toy Model
- train SIREN w/ toy model
  - NO stat. fluctuation
- compare SIREN output to the analytical model
- ≤ 1% bias
- systematic error for SIREN
SIREN Performance w/ Statistical Uncertainty

**Toy+Noise Model**

- train SIREN w/ toy+model
  - input data *with* stat. fluctuation
- compare SIREN output to the *input data*
- \( \leq 1\% \) bias at high visibility values
- bias increases gradually for lower visibility
  - comparable to the expected stat. err.
- contributions from both *statistical* and *systematic*
SIREN Performance
Learning the Underlying Distribution

Toy+Noise Model (Ref: Toy)
- train SIREN w/ toy+model
  - input data *with* stat. fluctuation
- compare SIREN output to the *analytical model* (i.e. the truth distribution)
- same bias as trained with Toy Model (i.e. input data w/o stat. uncertainty)
- statistical fluctuations suppressed

SIREN is able to learn the underlying distribution at ≤ 1% level, even with the imperfect input data.
Case 1: LUT == 0, SIREN high vis.

No light at the base / mount of PMT.
SIREN (as a continuous parameterization) tries to map the visibility toward max. visibility = 1.

Negligible impact on physics. It corresponds track hitting directly to the PMT, leaving NO ionization charge. Likely there is a fiducial volume in the high level analysis.
Case 2: SIREN Overpredicts Visibility

SIREN's limitation on sharp edge transition.
Module-0 Detector

**Short term goal**
- build a prototype of 2x2 array of detector modules
- test w/ NuMI neutrino beam at Fermilab

**Long term goal**
- build a 7x5 array (TBC) for the DUNE Liquid Argon Near Detector

*Figure 1.* Schematic of the $0.7 \text{ m} \times 0.7 \text{ m} \times 1.4 \text{ m}$ Module-0 detector with annotations of the key components.
Module-0 Charge Readout System

View from the top of Module-0

- 2 drift volumes (TPCs)
- separated by a cathode plane
- 4x2 LArPix tiles per anode plane
- 70x70 pixels per tile
- pixel pitch 4.43 mm
Module-0 Light Readout System

- 4 LCM and 4 ArCLight tiles per TPC
- each tiles ~300 mm x 300 mm x 10 mm
- 6 SiPMs per tile
- total of 48 SiPMs per TPC
Data Selection for Module-0

- data collected between 4/4/21 - 4/10/21 at Bern
  - “default” settings (0.5 kV/cm, med. threshold ....)
- cathode-anode crossing tracks in TPC-0
  - one clustered object per charge image
  - dbscan eps=25 mm, min_samples=5
- matching charge-light pairs by trigger timestamp
- ~680k tracks selected
  - training/validation/testing samples in 75-15-15 splitting ratio
  - for track statistic study, splitting ratio is 20-80 for training/testing
Note on SiPM Indexing

** Grayed out points are excluded from this analysis
  • unclustered points, or
  • portion of track in TPC-1
Charge-to-Light: SIREN v.s. LUT

- train a SIREN model using simulated data (i.e. LUT)
- point-source input
  - \( \{x_i, y_i, z_i\} \rightarrow \{\text{vis}_i^0, \text{vis}_i^1, \ldots, \text{vis}_i^{47}\} \)
- calculate charge-to-light prediction
  - \( \text{pred.} \sim \sum Q_i \text{vis}(r_i) \)
- \( \text{vis}(r_i) \): either from LUT or SIREN
- both methods are practically the same \(<1\% \text{ difference}\)
Calibration of SIREN Model

Calibration => Multi-parameters optimization problem of the SRIEN model

**Objective** minimize the difference between observation and prediction

**Prediction for SiPM-j**

\[
\text{pred}_j = Y_j \times \sum Q_i \text{vis}_j(r_i)
\]

- “effective light-yield” for 48 SiPMs (floating)
- visibility by SIREN ~7k parameters (floating)
- measured charge of the track (fixed)
- locations of charge deposition (fixed)

**Loss function**

\[
\chi^2 = \sum_j (\text{obs}_j - \text{pred}_j)^2 / (\text{pred}_j + \epsilon^2)
\]

\(\epsilon = 5\) p.e.