Learning Field Response and Laser Data

Brett Viren

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Topics

- Field response calculation
- Traditional methods to solving for fields
- Learning fields from Physics.
- Learning fields from real laser/detector data.

Field response in a nutshell

Field response (FR) gives us **current induced by a moving charge**.

FR is a critical component for:

- *forward* **simulation** to transform ionized electrons in to measured ADC waveforms.
- *inverse* **signal processing** to reconstruct drifted electron distribution.

Traditionally, FR is calculated by stepping through a **drift potential** (velocity field) and combining with a **weighting potential** (Shockley-Ramo).

Potentials are found by **solving the Laplace equation** satisfying boundary conditions.

- *drift* potential uses applied voltages
- *weighting* gives 1V to electrode-of-interest, grounds all others.

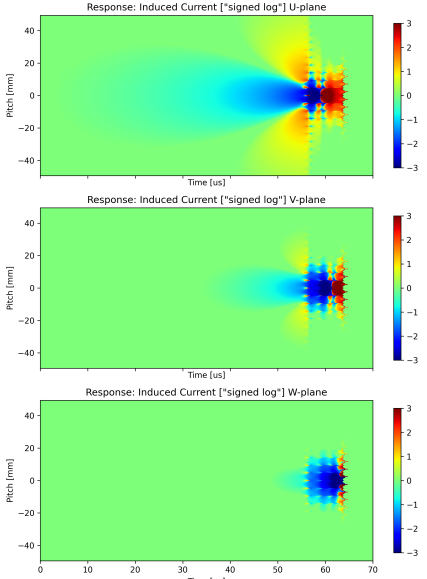
Traditional Laplace solutions methods

Various methods exist and BNL runs/writes/wrote several that serve the LArTPC community:

- **GARFIELD** (FEM, ST CPU, FORTRAN) provides all LArTPC 2D models for wires.
- **poichoir** (FDM, MT CPU/GPU, PyTorch) provides hybrid 2D/3D for strips and pixels.
- larf (BEM, ST CPU, Python/C++) earlier experiment for 3D wire models.
- drifiers (FEM, ST CPU, C++) earlier Garfield++ based implementation that never quite reached escape velocity.

Example 2D FR for wires

- Calculated by GARFIELD.
- U, V and W planes.
- Long range effects.
- Bipolar contributions even to “collection” plane.



New approach: **learn** fields

Learn potentials $\Phi_\theta(\mathbf{r})$ by optimizing parameters θ against a loss function $\mathcal{L}(\Phi_\theta)$.

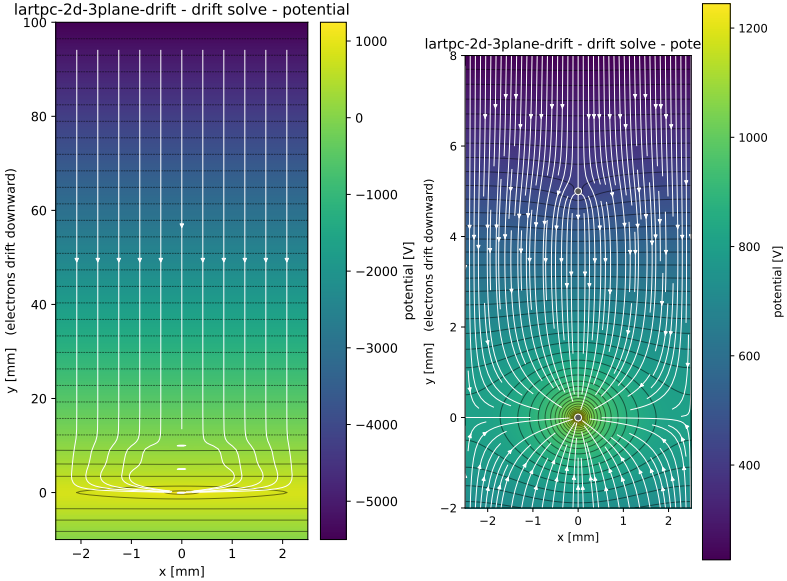
Machine learns physics

Loss function with **Laplace** and **boundary comparison** terms.

Machine learns detector

Loss function compares a **prediction** to **real detector output**.

Physics-informed learning of 2D wire drift solution

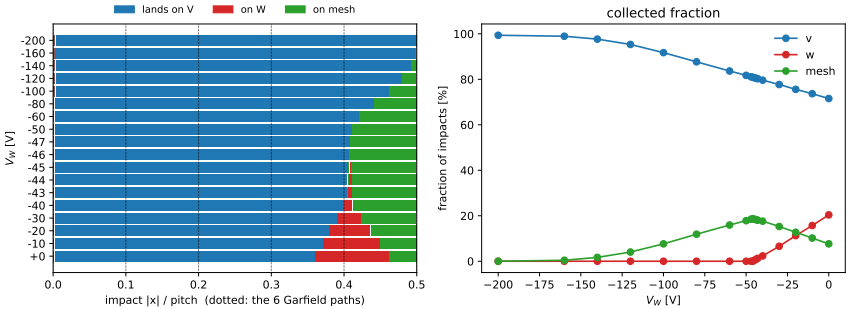


Learning parameterized field response against physics

Simplest case, learn potentials $\Phi(\mathbf{r})$ as a function of position $\mathbf{r}$.
But, $\Phi_\theta(\mathbf{r})$ can have and learn additional parameters θ:

- A floating W-plane voltage or other pathology.
- Design parameters (sizes, positions, voltages).

Collecting plane vs floating W-plane voltage and impact position



Learned the floating APA W-plane is at -47V[1].

- Simulation uses only 6 impact positions and assumes same-plane collection for all.
- Sigproc takes average over all impact positions.

→ Special high-resolution sim and FR can likely match real data on “bad” APA. TBD!

[1]Exact value depends on assumptions of mesh plane location and domain dimensionality.

Machine learns detector

Basic approach

1. Forward simulation/model to predict ADC waveforms.
2. Compare predicted and measured ADC and generate loss/error.
3. Optimize simulation parameter.

Bonus if model is *differentiable* to allow fast *backpropagation* of errors to parameters.

Where the laser can help

- Limiting the number of model parameters is important to make the learning tractable.
- Laser shots can provide well-characterized sources that are easy to simulate for the forward model.

Learning against laser data

I expect physics-informed learning is sufficient to calculate FR when:

- Design is simple (including existing wires, strips+holes, pixels).
- Design is nominal or a simple variant is understood (including floating W-plane).

Learning FR from real data can confirm or contradict even simple FR calculations.

- Already found learning a 15-20 tick discrepancy rules out 0V W-plane model.
- Learned APA1/anode0 V has 0.875 ± 0.004 of APA2/anode2 W near mutual boundary.

Laser can be an important contributor when:

- The one case were we can a'priori make paired sim/data paired events.
  - Unpaired learning, eg with cosmics, is possible but rather more complicated.
- A high-parameter count model needs multiple sources to disambiguate parameters.

Data quality is important to apply laser data to FR learning.

Some findings in the PDHD laser data

Probably not news to this group, but I ran into these issues:

- Logged directions are off by a nearly constant 37 mrad.
- Port positions are off by centimetres across the beam.
- Arrival jitter is up to about 35 μs.
- Intensity (at least in early data) about 100× MIP, ADC saturated.
- Laser track bends and at a fixed drift distance, about 620 mm from the anode, and appear alike on U, V and W.
  - Already understood? Field cage defect? Localized space charge?

Some work-arounds developed:

- The model can fit/learn direction/position/time/intensity as nuisance parameters.
  - But, this reduces its power for learning primary parameters.
- Event selection and track segment masking.

Suggestions for PDVD laser runs

Unlike wires, FR for strip designs have moderate variation in 3rd, along-strip dimension.

- Shoot laser parallel to a view's strips to resolve sub-pitch FR features.
- Exact shot-shot repeatability at any angle can also help resolve this.
- Extreme directions are useful: isochronous/parallel and elongated/normal.
- Measuring shot-to-shot intensity/time/direction would remove nuisance parameters.
- Keep intensity below ADC saturation.
- Change rep-rate to see if bends are due to laser-induced space-charge.

Summary

- Physics-informed learning methods provide better FRs than traditional.
  - Higher resolution, precision, accuracy. Solves parameterized variants.
  - Wires and pixels well covered, VD strip+holes is next.
  - Solutions finish rather quicker than traditional methods.
- Data-informed learning can be important in certain cases.
  - Confirm/contradict overly simplistic physics-informed models.
  - Handle pathology not easily modeled from first-principles.
  - Learn more than FR (eg, space-charge effect)
- Laser data can contribute to this story with high-quality data, sub-pitch resolving.
  - PDVD's variation along a strip makes this more important than for wires.

$\mathcal{FIN}$

Backups

Field response: current induced by a moving charge

In LArTPC, drift velocity is a function of a *drift potential* Φ_d (and electron mobility)

$$\mathbf{v}_d = \mu \mathbf{E}_d = -\mu \nabla \Phi_d$$

$\rightarrow$ solve Laplace equation with boundary electrodes at applied potential

- Symmetries typically allow domain to span 1-wire/strip.

Shockley/Ramo: induced current in electrode k is function of a *weighting potential* $\Phi_{w,k}$

$$I_k(t) = q\, \mathbf{v}_d \cdot \mathbf{E}_{w,k}; \qquad \mathbf{E}_{w,k} = -\nabla \Phi_{w,k}$$

$\rightarrow$ solve Laplace equation with electrode k at 1V all others at ground.

- Symmetries and long-range induction typically require 0 +/- 10 wire domain.

Step tabulation of paths starting on grid of *impact positions*

Typically 100ns samples over 10cm drift and 10 impact positions per wire region.

Machine learns physics - the model

Decompose: $\Phi_\theta(\mathbf{r}) = B_c + N_\theta$.

N_θ is a multi-layer perceptron with sinusoidal activations (SIREN)

Analytic, infinitely differentiable.

- Relatively small network, few parameters to learn, fast to train.
- Bad at representing high-bandwidth functions (mix of fast peaks and slow curves).

B_c an exact analytic solution to parts of the geometry.

Eg, potentials of an infinite wire, parallel plates.

- Provides harmonic solutions terms, by construction ($\nabla^2 B_c = 0$).
- Can be augmented to assure boundary conditions are met.

B_c **"soaks up" the high-bandwidth part** and **SIREN learns a smooth correction**.

Machine learns physics - the loss

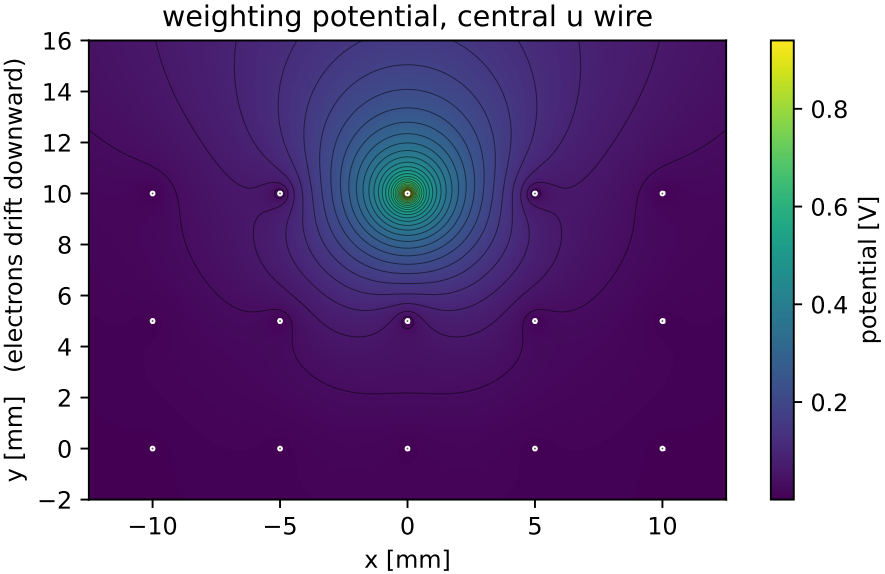
$$\mathcal{L}(\theta, c) = \lambda_\Omega \left\langle \left(\frac{p^2}{V_{\text{ref}}} \nabla^2 N_\theta \right)^2 \right\rangle_\Omega + \lambda_\partial \left\langle \left(\frac{\Phi_\theta - g}{V_{\text{ref}}} \right)^2 \right\rangle_{\partial\Omega} . \tag{1}$$

- First term drives Laplace to zero. Note, $\nabla^2 B_c = 0$ by construction.
- Second term drives solution to meet the boundary data, g.

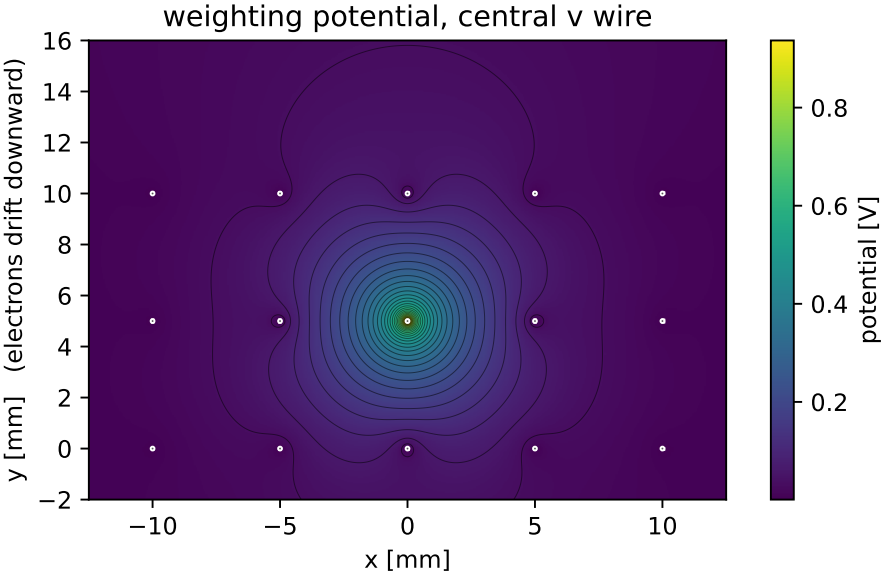
Can get rid of the λ hyper-parameters by using **distance functions**.

- Geometry and boundary then fully captured by B_c and distance functions.
- Rest of the solving machinery then independent of detector and dimensionality.

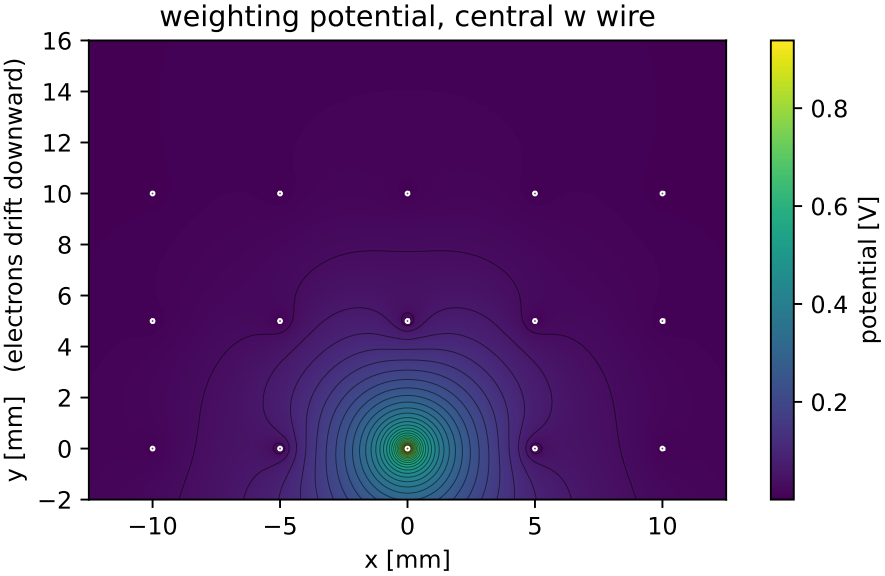
2D wire weighting solution - U



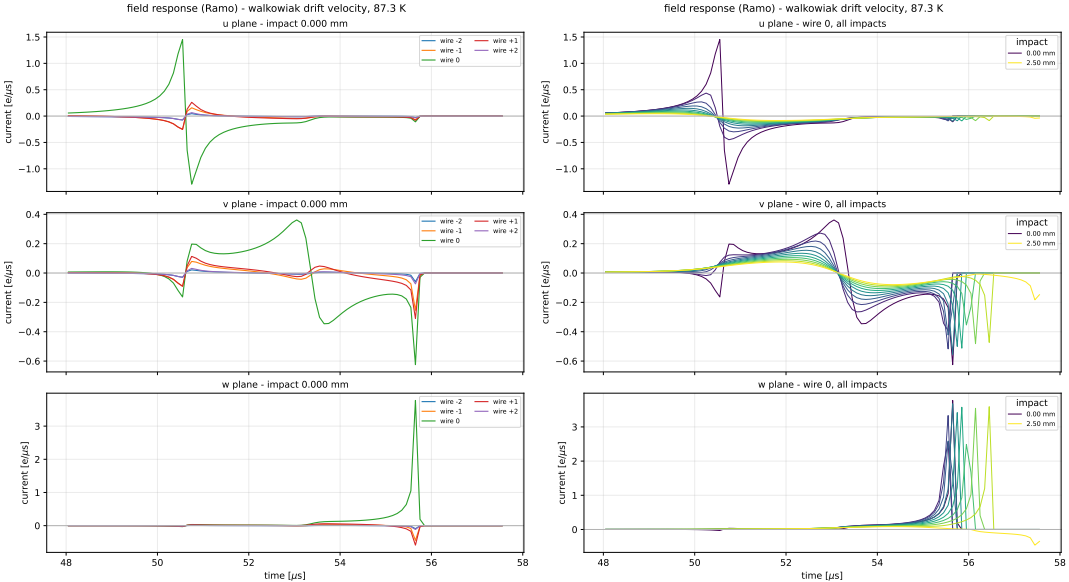
2D wire weighting solution - V



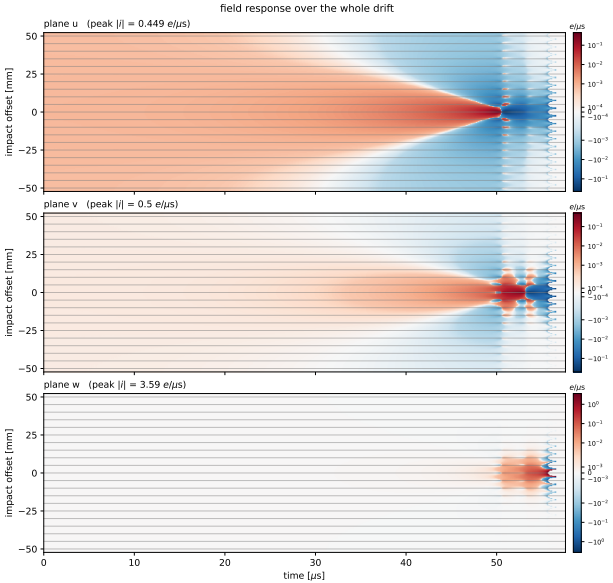
2D wire weighting solution - W



2D wire field response waveforms



2D wire field responses, tablulate



Laser track bends

