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Unfolding the Electromagnetic Field from Voltage Time Traces using a Neural Network Approach

Maximilian Straub,[a,*] Martin Erdmann,[a] Katharina Hafner[a,b] and Josina Schulte[a]

[a] *RWTH Physics Institute III A, Otto-Blumenthal Str., Aachen, Germany*

[b] *now at University of Bremen, Institute of Environmental Physics (IUP)*

E-mail: straub@physik.rwth-aachen.de, hafner@iup.physik.uni-bremen.de

The *Auger Engineering Radio Array* (AERA) is part of the Pierre Auger Observatory and is designed to investigate cosmic-ray induced air showers using radio measurements. The ultimate goal of AERA is to recover the three-dimensional electromagnetic field originating from the air shower with the measured voltage time traces of the antennas, which is a challenging task. The electric field measurements are modified in the detection process by the frequency- and direction-dependent antenna response, and is superimposed by noise. We use conditional Invertible Neural Networks (cINNs) to learn posterior distributions, from which the most likely electromagnetic field given a measured voltage time trace can be inferred. We extend the method with an autoencoder to further enhance robustness, reduce the parameter space, and decouple the cINN from data shape. We will present an overview of the method and its application to simplified simulation data with typical properties of AERA and evaluate the methods reconstruction quality.

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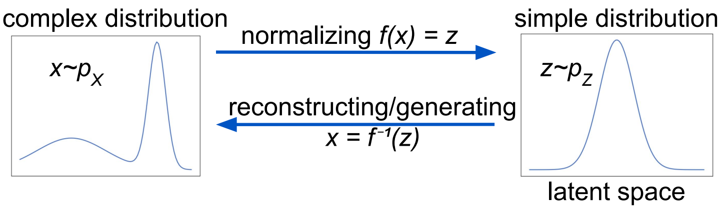

Figure 1: Schema of a normalizing flow. The forward direction maps a complicated function onto a simple function while the backward direction is used to generate or reconstruct samples of the complex distribution.

1. Introduction

Upon entering the atmosphere, ultra-high energy cosmic rays (UHECRs) induce extensive air showers by interacting with air molecules. Charged particles in the air showers emit radio waves by two well-established mechanisms, the geomagnetic emission and the Askaryan effect. At the Pierre Auger Observatory [1] radio emission is detected by the Auger Engineering Radio Array (AERA) [2]. The aim of this work is to infer the electric field originating from the air showers using the voltage traces of the antennas. It was developed and analyzed with simplified simulated data using parameters typical of AERA.

The antennas used at AERA have two polarization directions, primarily to detect the horizontal components of the electric field. The third, mostly vertical component is not directly measured. Furthermore, the antenna acts like a filter, with a frequency- and direction-dependent complex gain. Finally, noise contaminates the measurements. For reconstructing the all components of the three-dimensional electric field, information on the arrival direction of the shower was previously needed which required at least three antenna stations to measure the radio pulse [3].

In this work, we present a method to unfold the three-dimensional electric field from the antenna voltage trace, i.e. remove detector and noise effects, using a single station only.

2. Conditional Invertible Neural Networks

The method presented here uses conditional invertible neural networks (cINNs) which belong to the network class of *normalizing flows* [4]. They conserve probability when mapping a complicated distribution onto simpler ones while being invertible. Using the inverse direction, samples from the original distribution can be drawn by sampling the simple distribution instead. This way, cINNs can be used for reconstruction. The process is illustrated in Fig. 1.

Conditional invertible neural networks are constructed to be bijective. In particular, they consist of several so-called *affine coupling blocks* [7] in a row. An exemplary block is illustrated in Fig. 2. The affine coupling block is a mathematical expression that takes functions (here s_i and t_i) and is invertible without the need of the embedded functions to be invertible. Neural networks are used for these functions.

The coupling block maps a vector $\mathbf{x}$ via

$$\begin{aligned} \mathbf{v}_1 &= \mathbf{x}_1 \odot \exp(s_1(\mathbf{x}_2)) + t_1(\mathbf{u}_2) \ , \\ \mathbf{v}_2 &= \mathbf{x}_2 \odot \exp(s_2(\mathbf{x}_1)) + t_2(\mathbf{v}_1) \ , \end{aligned} \tag{1}$$

where $\odot$ stands for element-wise multiplication. The inverse direction is given by

$$\begin{aligned} \mathbf{u}_2 &= (\mathbf{v}_2 - t_2(\mathbf{v}_1)) \oslash \exp(s_2(\mathbf{v_1})) \ , \\ \mathbf{u}_1 &= (\mathbf{v}_1 - t_1(\mathbf{u}_2)) \oslash \exp(s_1(\mathbf{u_2})) \ , \end{aligned} \tag{2}$$

where $\oslash$ stands for element-wise division.

The embedded functions are conditioned and take the condition c. The cINN will map the complex distribution onto the simple distribution under that condition. This condition is used when sampling the complex distribution via the inverse direction as well, producing conditioned samples.

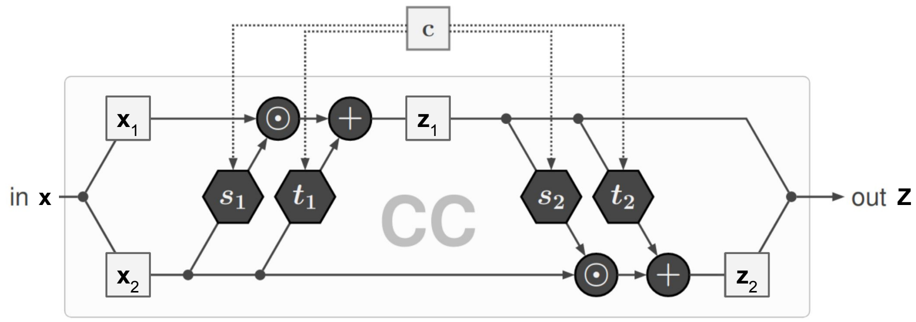

Figure 2: Conditional coupling block with RNVP architecture, forward direction. Adapted from [7].

3. Network Architecture

The network used here consists of two parts: An autoencoder [8] is used for dimensionality reduction, compressing each time-dependent voltage trace into a short list of uncorrelated numbers. The second part is a cINN, which can map between the encoded electric field and the encoded voltage measurements. Pytorch [5] and FrEIA [6] were used as frameworks.

An autoencoder contains two parts, the encoder and the decoder. The encoder consists of 5 layers of convolutions, iteratively reducing the 128-time bins of the input to 15 numbers, thereby mapping the input into a lower-dimensional space. The decoder consists of 5 layers of transpose convolutions, mapping the 15 numbers of the lower dimensional representation back into a full time trace. Another encoder is used as a pre-processing network for the condition input of the cINN. This pre-processing network is initialized with the weights of the autoencoder's encoder.

The cINN is a chain of 8 RNVP type [9] coupling blocks. Inside these blocks, fully connected networks are trained. Fig. 3 presents the combined architecture. The cINN network produces three compressed electric field traces, one for each direction, by sampling from the Gaussian distributions and by using the encoded voltage traces of the two antenna polarizations as condition. The autoencoder decompresses these to three full time traces. Thus, for a given antenna measurement, the combined architecture infers the most likely three-dimensional electric field vector as a function of time. This can be repeated multiple times with different Gaussian samples.

4. Reconstruction Quality

The method presented here produces a full three-dimensional electric field for a given two-dimensional voltage trace. The voltage trace is contaminated with noise and affected by the antenna

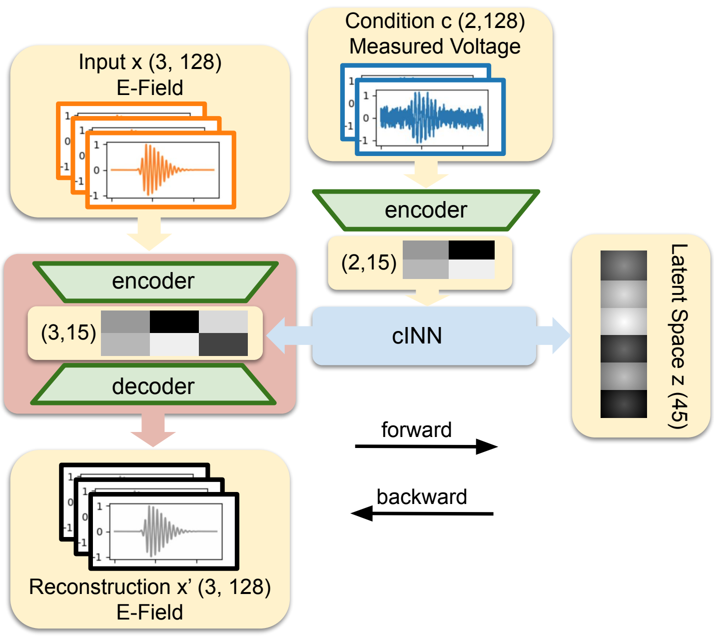

Figure 3: Model architecture. An encoder is used to compress time traces to a lower dimensional representation. The cINN learns the unfolding on this compressed data. To do the unfolding, the cINN produces a compressed electric field trace, which is expanded by the autoencoder's decoder into a full trace.

characteristics. The reconstruction presented here removes noise, corrects for detector effects, and gives an estimate for the third dimension that is not explicitly measured. Fig. 4 shows an exemplary reconstruction. Reconstructing the same trace multiple times with different Gaussian samples was used to estimate bin-by-bin uncertainties on the reconstructed electric field traces. These errors were found to be overestimated with respect to Gaussian errors per bin. In general, the electric field reconstruction worked well for sufficiently large signals above noise. We observed, that removing small signals from the training data improved the overall reconstruction quality. The reconstructions deviate on average less than 10% in the magnitude of the signal from the true signal. Correlations between reconstruction and truth were convincing for most traces, indicating that the shape of the signal was recovered well.

5. Summary

Extensive air showers produce radio signals that contain information about the shower development. When measuring this radio emission with antennas, the signals are modified by the antenna characteristics, superimposed by noise. Furthermore, only two of the three electric field components are measured directly by the two antenna polarizations. This work presents a method for the unfolding from the measured voltage traces to the corresponding electric field originating from radio emission from extensive air showers. The method uses an autoencoder for dimensionality reduction and a conditional invertible neural network for to produce the time-dependent electric field vector. The cINN operates on the lower-dimensional representation found by the autoencoder. The method successfully removed noise and other detector effects and produced an estimate for the the

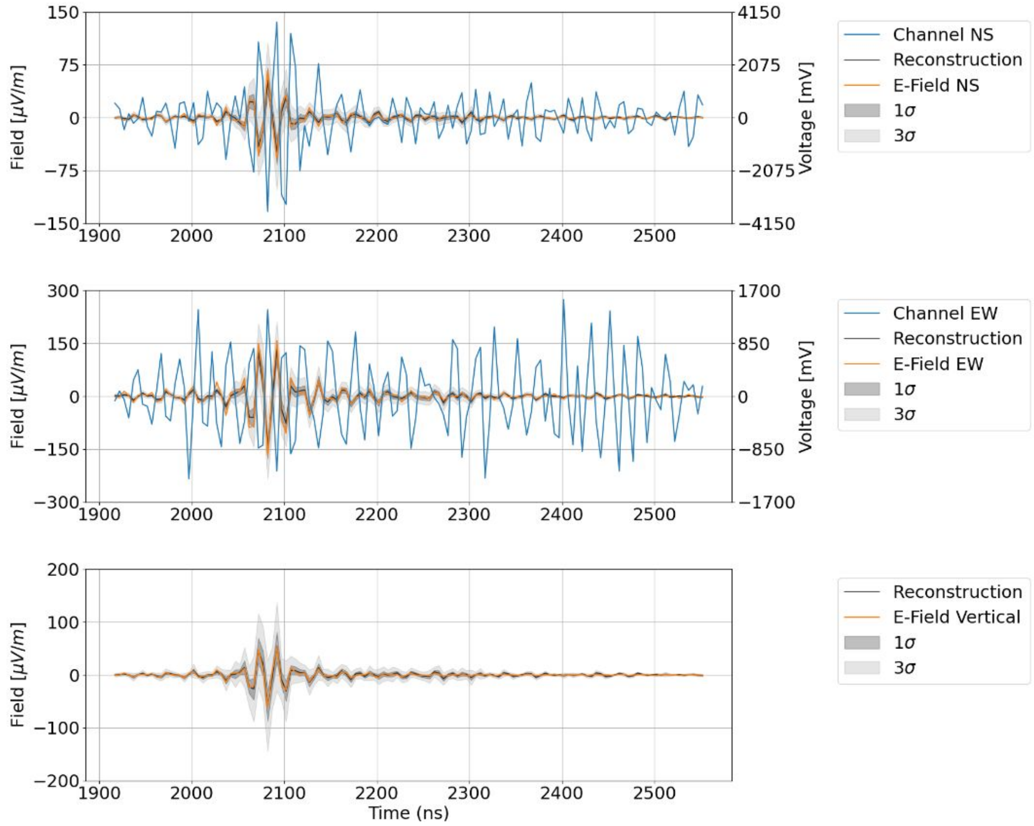

Figure 4: Exemplary reconstruction. The plot shows the two dimensional noise-contaminated voltage and the three-dimensional electric field and cINN reconstruction. The grey bands indicate error estimates by the network.

lost vertical direction of the signal. The performance was generally good, while signals with a small amplitude were unable to be reconstructed. Using an autoencoder for dimensionality reduction makes the cINN architecture independent of data shape, this way the method can be easily applied to other unfolding problems.

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