Autoencoder-extended Conditional Invertible Neural Networks for Unfolding Signal Traces

M Erdmann, K Hafner, J Schulte, M Straub

RWTH Aachen University, III. Physikalisches Institut A, Otto-Blumenthal-Str., 52074 Aachen, Germany

E-mail: katharina.hafner1@rwth-aachen.de, maximilian.straub@rwth-aachen.de

Abstract. The reconstruction of cosmic ray-induced air showers from measurements of radio waves constitutes a major challenge. In this work, we focus on recovering the full three-dimensional electromagnetic field from two recorded signal traces of an antenna station covering two horizontal polarization directions. The simulated field is folded by a direction and frequency-dependent characteristic antenna response pattern, resulting in voltage signal traces as a function of time. Both signal traces are contaminated by simulated background noise. We use conditional Invertible Neural Networks (cINNs) to learn posterior distributions, from which the most likely electromagnetic field given a measured signal trace can be inferred. To improve robustness, we extend the method with an autoencoder by reducing the parameter phase space and decoupling the cINN from specific data shapes. Thereby, each signal trace is condensed into a small number of abstract parameters in the latent space on which the cINN operates. The presented method shows promising results and can be transferred to other unfolding problems where the recovery of the pre-measurement state is of interest.

1. Introduction

Ultra-high-energy cosmic rays are the subject of current research. Open questions concern, e.g., their origin, acceleration mechanism, mass composition, and interactions with cosmic background fields. Upon entering the atmosphere, cosmic rays induce extensive air showers by interacting with air molecules. These interactions produce various types of secondary particles, which are measured with different detection devices. One measurement channel is the emission of radio waves, which originates from the separation of air shower particles with different electric charges. The mechanisms of radio emission are well understood through classical electrodynamics and are simulated accordingly.

A large array of antenna stations measuring radio emission from air showers is in operation at the Pierre Auger Observatory [1, 2, 3]. In each radio station, two horizontal polarizations of the three-dimensional electric field arriving at the antenna are measured.

In this work, we aim at reconstructing all three components of the electric field originating from the air shower, using only one radio station. Thereby, our method needs to remove the noise contamination, invert the direction and frequency-dependent antenna response pattern, and recover the third component of the electric field without relying on external information. Our analysis is based on simulated radio data of the Pierre Auger Observatory.

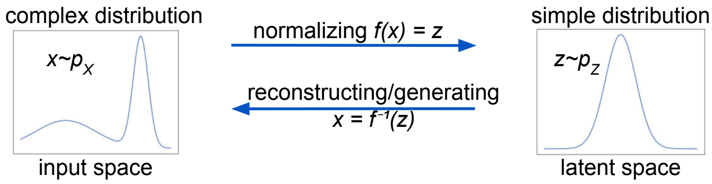

Figure 1. Schema of a normalizing flow. The forward direction (left → right) can be interpreted as a normalizing step while the backward direction is used to generate or reconstruct samples of the complex distribution.

2. Conditional Invertible Neural Networks

Conditional invertible neural networks (cINNs) are based on *normalizing flows* [4]. Normalizing flows are used to map complicated distributions to simpler distributions while being invertible. This procedure enables investigating the complex distribution by sampling from the simple one. Producing samples of the complex distribution can be especially useful for generating data samples or for reconstruction purposes [5, 6]. The process is illustrated in Fig. 1.

Conditional invertible neural networks are by design bijective and consist of chains of so-called *affine coupling blocks* [7]. The forward direction of one such block is illustrated in Fig. 2. The affine coupling block takes any functions s_i and t_i and embeds these in an expression that is invertible without requiring the functions themselves to be invertible. An input vector $\mathbf{x}$ is split into two halves $\mathbf{x}_1$ and $\mathbf{x}_2$ and processed by a block as follows:

$$\mathbf{z}_1 = \mathbf{x}_1 \odot \exp(s_1(\mathbf{x}_2, \mathbf{c})) + t_1(\mathbf{x}_2, \mathbf{c}), \tag{1}$$

$$\mathbf{z}_2 = \mathbf{x}_2 \odot \exp(s_2(\mathbf{z}_1, \mathbf{c})) + t_2(\mathbf{z}_1, \mathbf{c}), \tag{2}$$

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

$$\mathbf{x}_2 = (\mathbf{z}_2 - t_2(\mathbf{z}_1, \mathbf{c})) \oslash \exp(s_2(\mathbf{z}_1, \mathbf{c})), \tag{3}$$

$$\mathbf{x}_1 = (\mathbf{z}_1 - t_1(\mathbf{x}_2, \mathbf{c})) \oslash \exp(s_1(\mathbf{x}_2, \mathbf{c})), \tag{4}$$

where $\oslash$ stands for element-wise division. The exponential function is used to prevent division by zero in the inverse direction. The internal functions s_i and t_i used in this application are neural networks.

These functions receive on input, in addition to $\mathbf{x}$, a condition $\mathbf{c}$ which conditions the mapping from the complex distribution to the simple distribution. Therefore, the inverse direction maps a sample of the simple distribution under that same condition onto the corresponding complex sample.

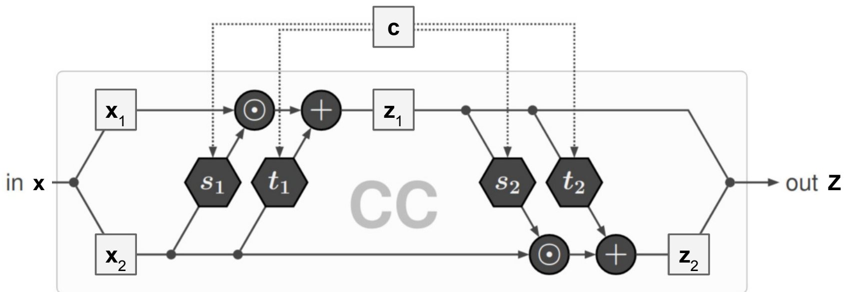

Figure 2. Conditional coupling block with Real Non-Volume Preserving (RNVP) architecture, forward direction. Adapted from [7].

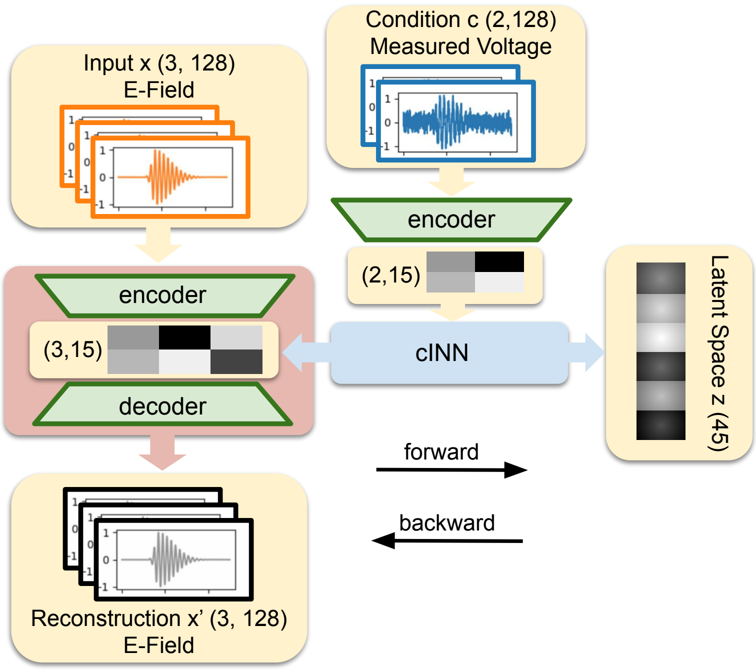

Figure 3. Full model architecture. An encoder is used to compress time traces to 15 variables. The cINN performs the unfolding between electric field and measured voltage on this compressed data. During the evaluation, the cINN produces a compressed electric field trace, which is expanded by the autoencoder's decoder unit into a full trace.

3. Network Architecture

The network architecture is shown in Fig. 3. It consists of an autoencoder [8] and a conditional invertible neural network; both were constructed using pytorch [9] and FrEIA [10]. The autoencoder is used to compress signal time traces into a list of uncorrelated variables, which are then processed by the cINN. The purpose is to reduce the number of parameters in the main network and decouple the cINN from the data shape.

The autoencoder contains an encoder and a decoder unit. The encoder consists of 5 layers of convolutions, iteratively reducing the 128-time bins of the input trace to 15 variables. Each layer except the last one uses a kernel size of 5, stride 2, and padding 2, while the last layer uses a kernel size of 8, stride 1, and no padding. The decoder unit consists of 5 layers of transpose convolutions, decompressing the 15 variables back into a full time trace, using the same kernels as the encoder in reverse order. The pre-trained encoder is further used to compress the input condition of the network. Note that in this case, the preprocessing encoder network remains trainable while optimizing the cINN.

The cINN consists of 8 blocks of the Real Non-Volume Preserving type (RNVP) [11]. The internal networks are fully connected with three hidden layers and 113 neurons each. It allows the reconstruction of three electric field traces, one for each directional component, under the condition of the antenna's two-dimensional voltage measurement by sampling from the Gaussian distributions. The trained cINN then produces the most likely electric field for the given measurement.

3.1. Training

During training, the forward direction of the cINN is used (Fig. 1). The loss function is derived from the Kullback-Leibler divergence and requires Gaussian shape of the resulting distributions [6]. The electric field of the training data is compressed by the encoder of the autoencoder and then passed on to the cINN. The voltage traces to be used as conditions are compressed by the encoder of the cINN. Then in the cINN, the compressed electric field is mapped under the condition of the compressed voltage onto Gaussian distributions. To stabilize training, the electric field traces and the voltage traces are normalized on input using the arsinh function, which acts like $\log(x)$ for large $|x|$. This normalization is reversible without loss in precision.

Training of the network is remarkably fast. The autoencoder and cINN were trained separately. The autoencoder and cINN were each individually trained for 20 epochs with a batch size of 100, with a combined training time of around 20 min on a GPU (NVIDIA GTX1080).

3.2. Evaluation

Reconstruction uses the backward direction of the cINN (see Fig. 1, reverse direction). The cINN encoder compresses the voltage traces which are passed as condition, and the cINN produces a compressed electric field. The autoencoder decoder decompresses the cINN output into a full electric field trace. These steps are repeated multiple times to approximate the posterior distribution of the electric field given the measured signal.

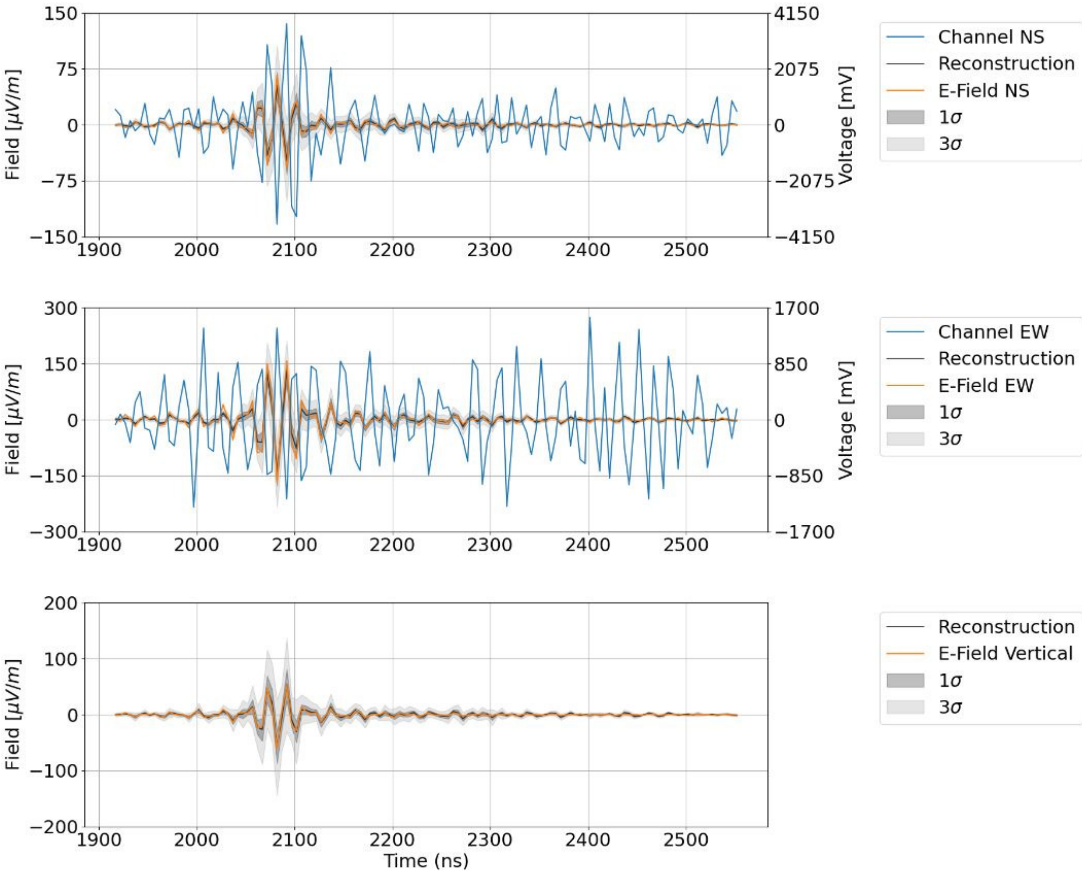

Figure 4. Exemplary reconstruction. The plot shows the two-dimensional noise-contaminated voltage and the three-dimensional electric field and cINN reconstruction. The grey bands indicate error estimates by the network.

4. Reconstruction Quality

The network is able to reconstruct the full three-dimensional electric field from a noisy two-dimensional voltage measurement of the antenna. It successfully removes noise and recovers the lost third electric-field component while removing frequency and direction-dependent antenna effects. Fig. 4 shows an exemplary reconstruction. The reconstruction worked well when requiring the maximum voltage amplitude to be above the RMS noise by a factor of ~ 1.7. Removing small signals from the training data improved the overall reconstruction quality. By sampling the Gaussian distributions many times for the same reconstruction, bin-by-bin errors were estimated for the reconstructed signal. These errors were found to be slightly overestimated. Quantitatively, around 90% of the true signal was contained in the network reconstruction's sigma band, which deviates from the expected 68% for Gaussian errors. Overall, the reconstructions deviate on average less than 10% in signal height from the true signal while the signal shape correlates perfectly in the time and frequency domain.

5. Conclusions

During measurement processes, detector effects influence the measured data. In this work, we presented a method to unfold the electric field of radio signals originating from an extensive air shower from measured voltage traces in antennas. With only two polarization directions available from the measurements, reduced information on the three-dimensional field is obtained. Beyond this, the antenna response pattern and noise contamination influence the recorded signal. The presented method consists of an autoencoder for data compression and a conditional invertible neural network (cINN) for reconstruction. The cINN operates on the reduced parameter space defined by the autoencoder. The method removed noise and other detector effects and recovered both the horizontal field components as well as the omitted vertical component of the signal. The performance was overall good for signals with a reasonable size above the noise. By using an autoencoder, the cINN architecture was independent of the data shape, and the method looks promising for other unfolding procedures. For more details and an extended discussion of the presented method, refer to [12] and [13].

Acknowledgments

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