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Interpolation of loudspeaker level balloons from polar measurements by using deep learning

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**ABSTRACT**

Complete radiation balloons are needed to analyze the performance of loudspeakers and to perform accurate tunning and electroacoustic predictions of loudspeaker systems. A method is proposed to obtain full radiation balloons from horizontal and vertical polar measurements by using U-Net, a deep learning architecture widely applied for image processing. Mean absolute errors lower than 4 dB were obtained on test data.

# Introduction

Radiation patterns are fundamental in the design process of loudspeakers, both as targets and as real measurements to verify their performance and to tune them properly. Electroacoustic simulation software based on loudspeaker models relies on radiation data to perform calculations of SPL and other acoustic parameters. These data should include complete radiation balloons in order to provide accurate results. A 5º resolution on Phi, Theta angles in spherical coordinates is proposed by the Loudspeaker polar radiation measurements AES standard [1] to fully characterize a loudspeaker radiation.

While the measurement of horizontal and vertical polars of a loudspeaker can be run with a single turntable in a relatively short time, the measurement of full radiation balloons requires complex acquisition devices to turn the loudspeaker or the microphones, with long set up time, providing a large set of measurements on the surface of a sufficient distant sphere. The number of measurements and the time needed is significantly longer than for only horizontal-vertical polar measurements. Another alternative is the use of a near field scanners [2] , [3] which are not affordable for many companies or institutions, and also produce large datasets with long measurement times.

Having a function to map 3D balloons from polar measurements could be really convenient in terms of development time, equipment and data volume. Neural Networks, as universal approximators [4], are considered in this work for the task. While great efforts have been done to apply Neural Networks to predict or interpolate Head Related Transfer Functions (HRTF) from sparse measurements [5], [6], [7], [8], these methods have not been applied to loudspeaker radiation prediction, as far as this author knows. This work presents a method to approximate full 3D SPL balloons from horizontal and vertical measurements by using convolutional neural networks.

# Method

In the proposed method, radiation balloons are represented as images showing SPL in colours as function of frequency in the x axis and the different measurement points in the y axis as rows. Measurements with only polar data show the response at vertical and horizontal corresponding polar points. This way, the problem has been reduced to an incomplete-image recovery problem.

A dataset of images has been created from full balloon measurements acquired as described in [9]. Input data images contain information only at the rows representing data at Phi= 0º, 90º, 180º, 270º (polar measurements), and Theta=0º, 180º (redundant on-axis and rear measurements), with any other rows set to zero. Output images contain data of all measurement points. Measurements are re-arranged in spiral order as described at [7] . Figure 1 shows an example of a full radiation balloon transformed to be used as image data by the proposed neural network.

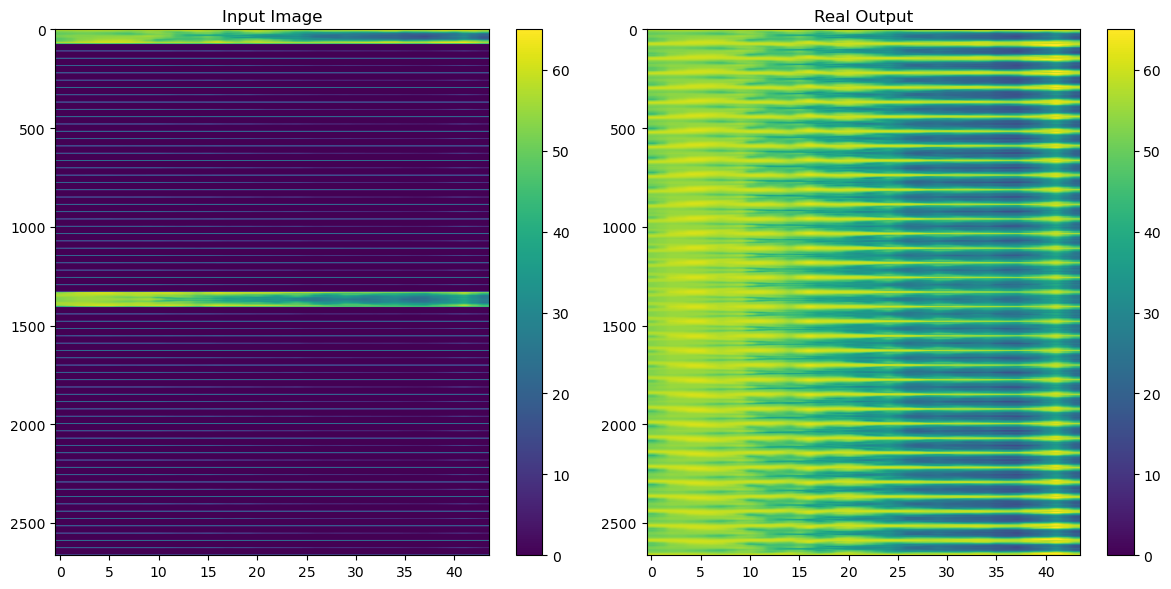


Figure 1. Example of input image (only polar data) and real output (full 3D balloon).

In order to recover full images from only polar images, a convolutional neural network with an architecture similar to U-net [10] has been trained by using balloon data from 7 loudspeakers: 5 were use as training data, 1 as validation data, and 1 as test data (unseen by the neural network in the training process). U-net deep learning architecture has proved its efficiency at image problems with short data sets. Basically, it consists of an encoder path followed by a decoder one, with direct connections between them (skip connections) to pass features from encoders to decoders.

The details of the proposed u-net can be seen at figure…

Meter aquí arquitectura

Data were normalized between 0 and 1 for training. Activation functions where Leaky Relu for encoder layers, Linear for decoder layers and Sigmoid for the output layer.

As input data are already showing level variation in dB, mean squared error (MSE) was used as loss to penalize large deviations.

# Results

Figure 2 shows training data with actual and predicted outputs.

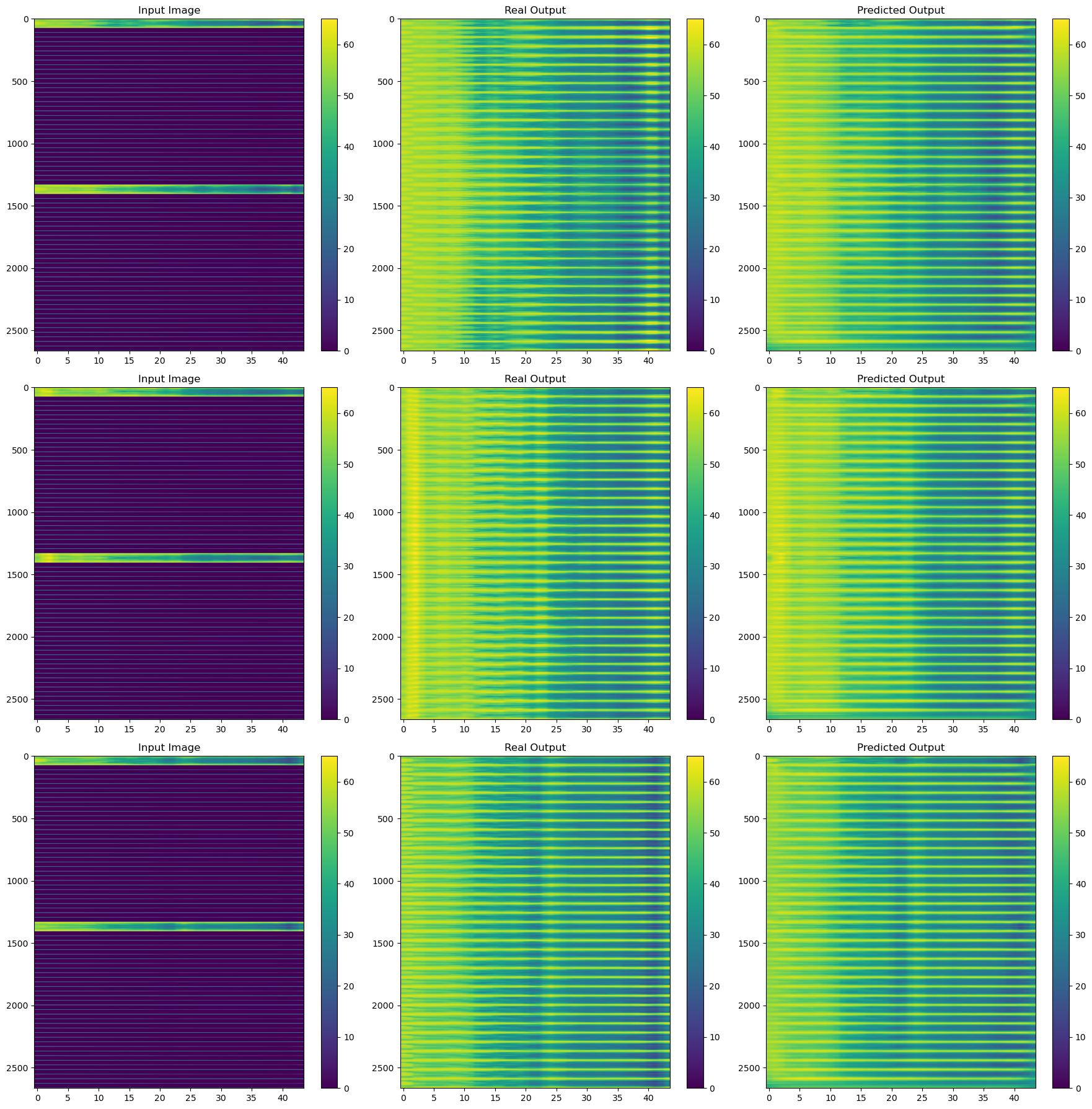


Figure 2. Training data images 1-2-3. Left column: only polar data. Central column: ground truth. Right: U-net prediction.

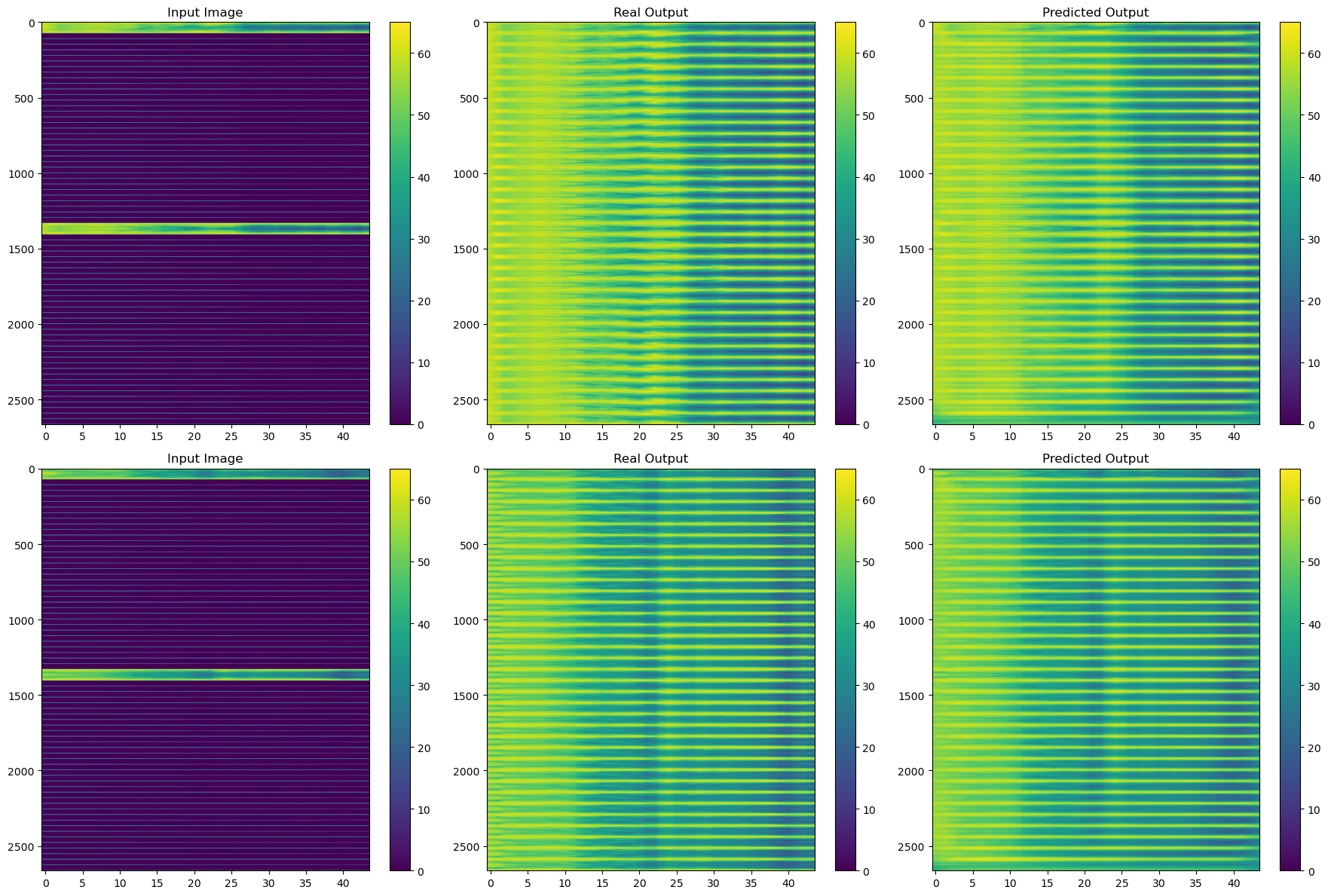


Figure 3. Training data images 4-5. Left column: only polar data. Central column: ground truth. Right: U-net prediction.

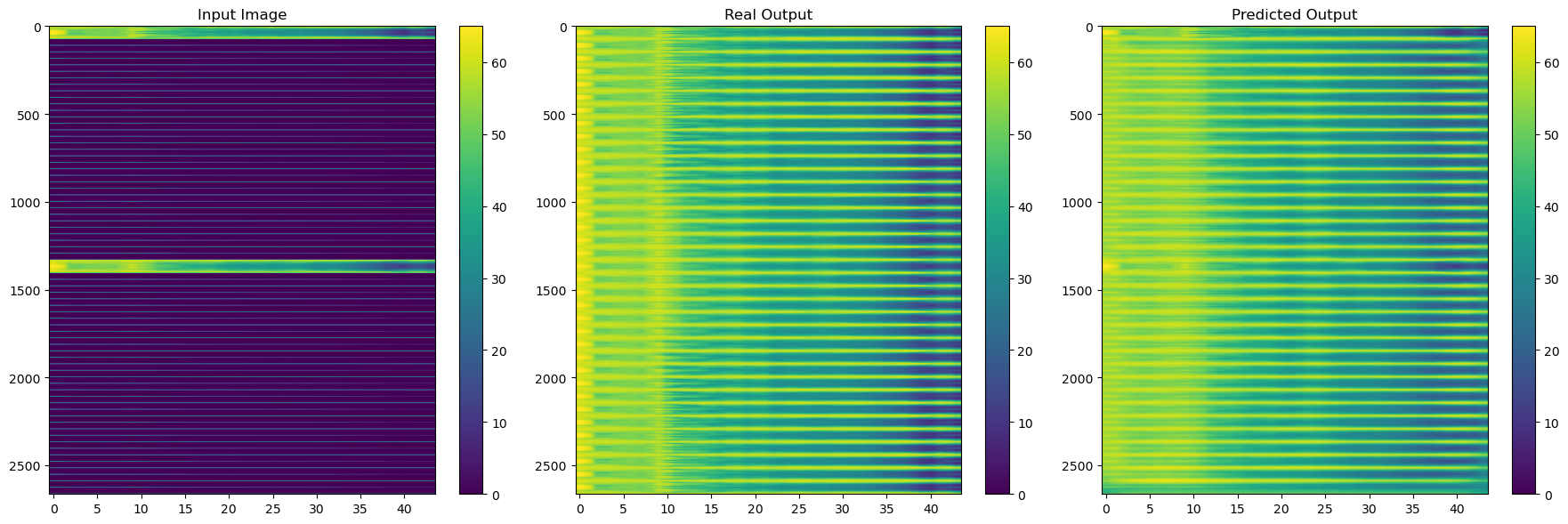


Figure 4. Validation data.

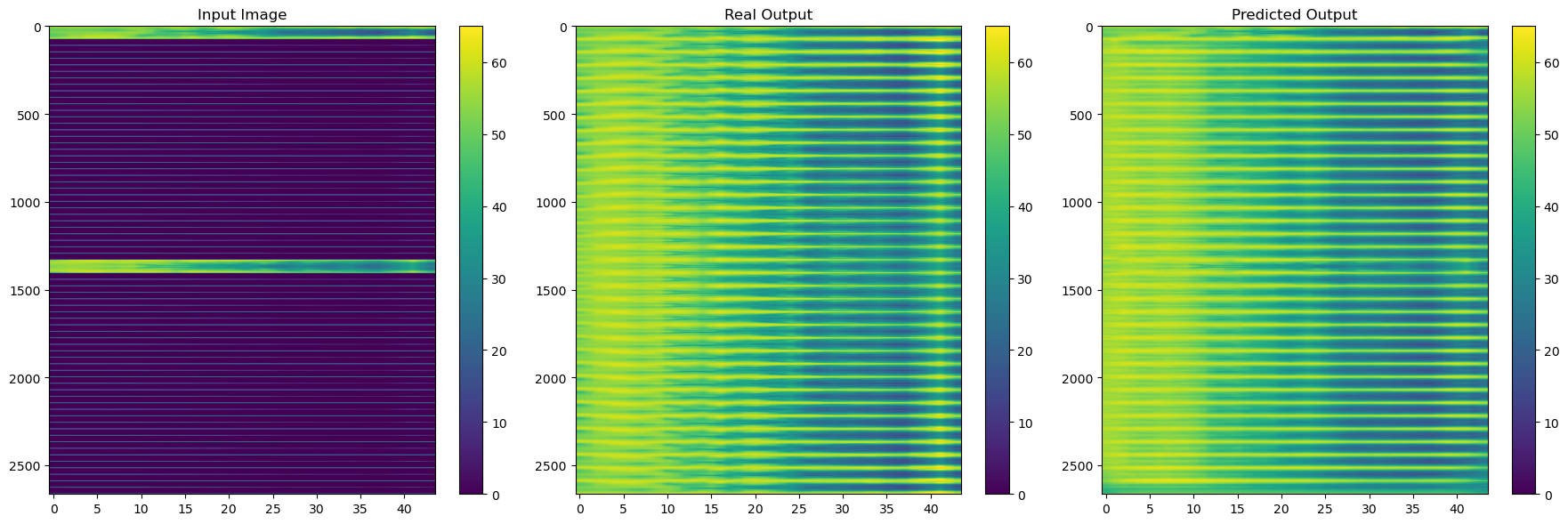
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Figure 5. Test data (line array unit).

Figures 3-4 present validation and test data predictions.

A first look shows that the neural network can approximately fill the incomplete images. To quantify the errors between true and predicted images, mean absolute errors (MAE) from MSE are listed below:

|  |  |
| --- | --- |
| Training data | 2.8388824 dB |
| Validation data | 4.012279 dB |
| Test data | 3.7689905 dB |

With the proposed method a MAE lower than 4 dB can be achieved on test data (unseen by the NN during training process) for a line array unit (with strong differences between horizontal and vertical coverages at high frequencies). With more conventional loudspeakers the MAE is even better. Falta hacerlo

For a more convenient understanding of results, polar plots at the plane defined by Phi=45º are shown at Figures 5-11.

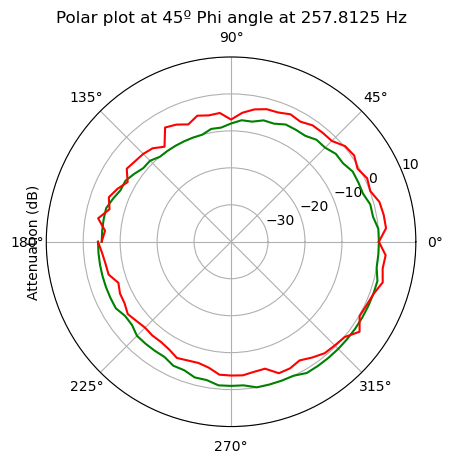


Figure 6. Polar plot at 250 Hz.

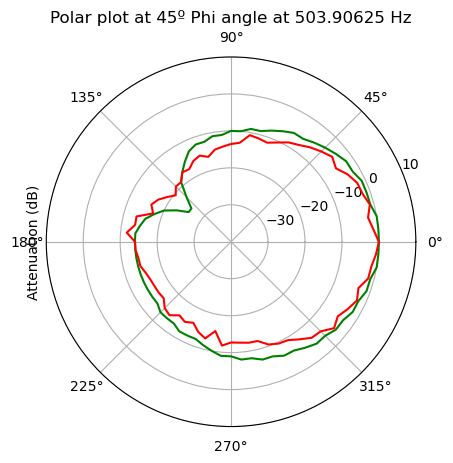


Figure 7. Polar plot at 500 Hz.

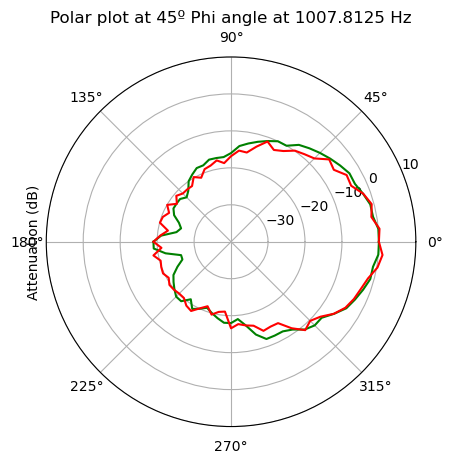


Figure 8. Polar plot at 1000 Hz.

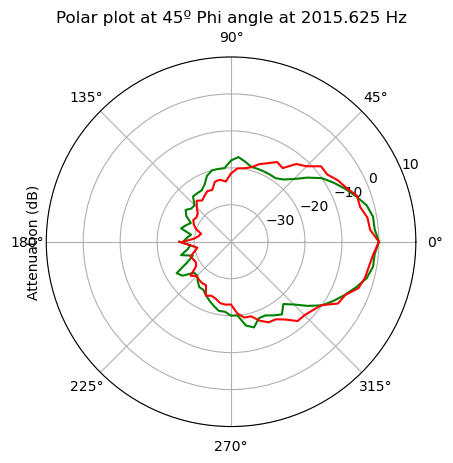


Figure 9. Polar plot at 2 kHz.

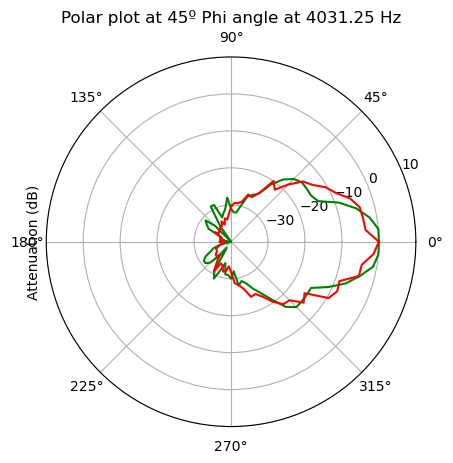


Figure 10. Polar plot at 4 kHz.

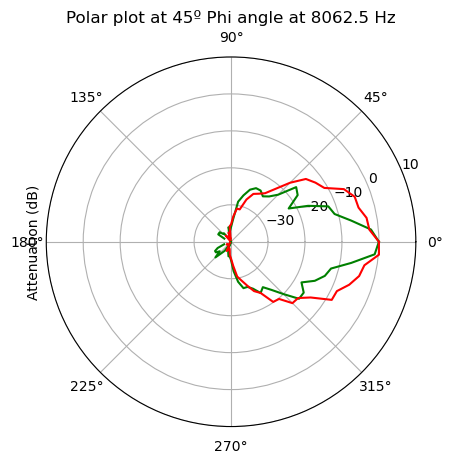


Figure 11. Polar plot at 8 kHz.

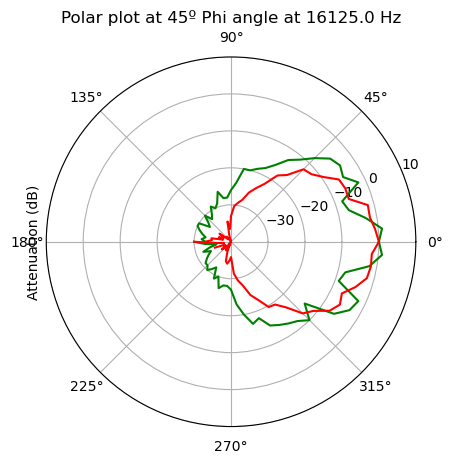


Figure 12. Polar plot at 16 kHz.

The plane at Phi=45º (combined information of measurements at Phi=45º and Phi=225º) is just in the middle of the horizontal and vertical polar measurements and contains, therefore, the predictions at the farthest points from provided measurements.

# Conclusions and further research

Neural Networks can be used to approximate level loudspeaker radiation balloons from polar measurements. In particular, U-net deep learning architectures can provide MAE lower that 4 dB over full balloons.

At high frequencies, with steeper variation of SPL against angles, the performance of the proposed network is lower. Refined architectures, more data and farther research are needed to improve accuracy.

Similar methods could be applied to phase interpolation in order to get complex responses.

More powerful models could be achieved by combining true polar measurements and full 3D simulations (from Finite Element Method software, for example) as input data, to obtain more accurate predictions. In this case, simple polar measurements would refine 3D simulations.

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