DEEP LEARNING PROPAGATION MODELS OVER IRREGULAR TERRAIN

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ABSTRACT

Accurate path gain models are critical for coverage prediction and radio frequency (RF) planning in wireless communications. In many settings irregular terrain induces blockages and scattering making it difficult to predict the path gain. Current solutions are either computationally expensive or slope-intercept fits that do not capture local deviations due to terrain variation, leading to large prediction errors. We propose to use machine learning to learn path gain based on terrain elevation as features. We implement different neural network architectures with dense and convolutional layers that could include effects difficult to describe with traditional models (e.g. back scatter). We test our framework on an extensive set of measured path gain data and consistently predict with 5 dB Root Mean Squared Error, an 8 dB improvement over traditional slope-intercept solutions.

***Index Terms*—** Propagation, deep learning, wireless communications

1. INTRODUCTION

Propagation modeling is a fundamental field of study in wireless communication as it determines signal to noise ratio, throughput, probability of error and other metrics, crucial for system design and implementation, evaluation and algorithms comparison [1]. Particularly, accurate models are crucial for coverage prediction and RF planning. Unfortunately, blockages, diffraction and scattering coming from rough irregular surfaces make accurate prediction a challenging task. The extensive prior work on propagation modeling has yet to provide computationally efficient and accurate models for prediction.

Traditional wave propagation models, based on integral equations [2] and parabolic equation [3], [4], [5] are computationally expensive. Other approaches are empirical models, based on extensive measurement campaigns and slope intercept fits to the data. These models perform acceptably in the measured environment but usually do not generalize to different locations without significant loss in accuracy. Generic models for rural areas exist, but they are still too general and have a high Root Mean Squared Error (RMSE) because they lack specific site information. Furthermore, none of the aforementioned models accounts for difficult to describe effects coming from the terrain as back scattering.

Machine learning models have been successful for their ability to learn features from difficult to describe data as images [6], video [7], and natural language [8]. These models are able to extract patterns and model relations among high-dimensional feature vectors like arrays of pixels. In our case, we have a large array of quantized heights from the terrain describing the environment. The main contributions of this paper are summarized as follows.

- We propose a novel machine learning framework for outdoors path loss prediction over irregular terrain that takes the terrain profile and distance between transmitter and receiver as features.
- We consider different and unexplored features and network architectures for this particular problem that exploit the spatial correlation among features.
- We provide a cross validation scheme for the neural networks and a comparison with a slope intercept fit to the data as a baseline solution as an empirical evaluation. We perform our experiments on real measurements, a data set comprising over 3000 links on the Canary Islands. We show that deep learning models outperform the baseline model by more than 8 dB.

We show that with a modest data set, deep learning models are able to learn the parameters very fast (minutes on laptop CPU). Once the neural network parameters are obtained, prediction for new cases is just an evaluation of the neural network response, which is rapid, in the order of milliseconds for one prediction. Furthermore, the network architecture allows for modeling effects not considered in traditional models such as as back scatter.

2. RELATED WORK

Traditionally, propagation models can be split in two categories: deterministic and empirical. Deterministic models rely on theoretical physical principles to model wave propagation and can be very accurate. Some analysis inspired models are the two ray model or ground bounce model [9]. On the irregular terrain setting, models based on integral equations [2] and parabolic equation [3], [4], [5] have been proposed and can account for some propagation effects but are computationally very expensive.

Empirical models are derived from experimental data like the Okumura [10] model or Hata model [11] and are easy to compute. However, they lack generalization to new environments. Some models, like the COST-231 [12] add empirical corrections to adapt to certain environments but these corrections are still too general to describe various site-specific settings.

Machine learning techniques have been proposed for propagation modeling [13] but it is still not a widely explored field. Some authors have used learning models to predict path gain from environment features [14] [15], [16], [17], [18], [19]. Neural networks consistently perform more accurately and efficiently than traditional models. However, this work only considers traditional and engineered features, as antennas heights, distance between transmitter and receiver, land usage and vegetation information, and collecting this information is not easy.

3. PROBLEM FORMULATION

We consider the regression problem of predicting path gain between a transmitter TX and a receiver RX given the terrain profile, obtained as the intersection of the terrain elevation map and a vertical plane containing the locations of both transmitter and receiver. For omnidirectional antennas being considered, path gain is the difference in dB between the received power and transmit power.

Formally, let P be the path gain between the transmitter and receiver. Let $\vec{x} = (x_1, ..., x_n)$ be the terrain profile between the transmitter and receiver, taking terrain heights every d meters through a vertical cut. Let r be the distance between transmitter and receiver.

We implement different neural networks to approximate a function $f : \mathbb{R}^n \to \mathbb{R}$ such that $f(\vec{x}, r) = P$.

For this task we train several neural networks architectures to minimize mean squared error. Dense layers are commonly used to capture and extract non linear, difficult to describe relations among features [20]. The motivation for using convolutional layers in our problem is their ability to account for local or repetitive patterns in spatial and temporal features [21]. Consequently, we propose convolutional layers in our problem because propagation depends on local patterns, like valleys that enhance signal strength.

4. MODELS

4.1. Features Encodings

To predict path gain we use terrain heights describing the profile between transmitter and receiver by taking a vertical plane cut through both antennas' locations. Neural networks need to be trained on equal length sequences. Consequently, to avoid different length profiles we use zero-padding, to make all profiles the same length. However, to distinguish from profiles where the actual height is zero, we add an additional feature, the distance r between transmitter and receiver. We illustrate this in Figure 1. For the convolutional network, we first extract features from the zero-padded profile and then concatenate the extracted features with r, the distance between transmitter and receiver. This feature vector is fed to a feed forward network for the final path gain prediction.

4.2. Network Architectures

We tested different feed forward networks architectures with different number of neurons and fully connected layers. We also implemented architectures with convolutional layers as first layers, followed by dense layers, also varying the number and size of layers, filters and kernel size. All networks used ReLU activations. We split the data on 5 folds and, after trying with varying architectures, we selected the networks that minimized cross validation error over the 5 folds.

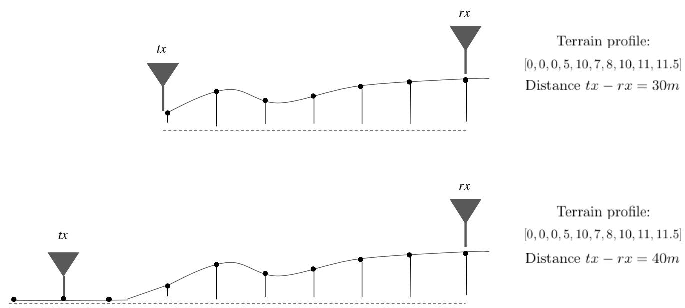

Fig. 1. *Example of two different transmissions features. Zero padding before gives rise to the same profile so we add distance between the transmitter and receiver as an additional feature*

We found that for the feed forward network with two hidden layers with 256 and 32 neurons respectively had the best performance. Deeper architectures did not improved accuracy and the variance of results across cross validation folds was larger. Wider networks overfitted. For the convolutional network we found that the best performance with the following hyperparameters: a single convolutional layer with kernel size of 3, 8 filters, followed by max pooling with window size 2. This output was flattened and concatenated with r, the distance between transmitter and receiver and then fed to a fully connected network with two layers, with 256 and 64 neurons respectively. In this case, adding more convolutional and pooling layers increased training time considerably, several minutes, and the accuracy was about the same or worse. Adding more dense layers overfitted the training data. Figure 2 and Figure 3 illustrate the networks' architectures used and reported on Section 5.

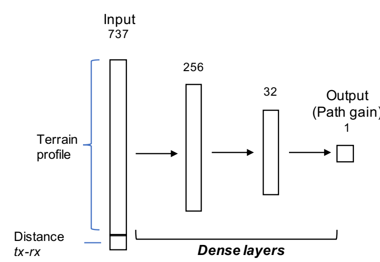

Fig. 2. *Feed forward neural network architecture.*

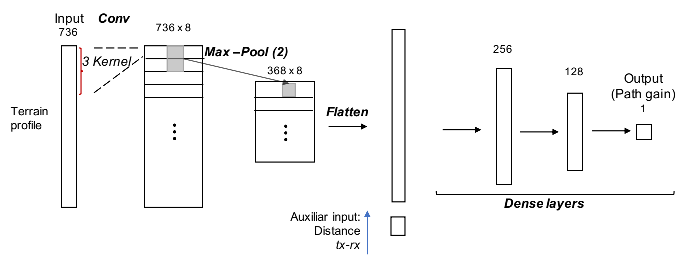

Fig. 3. *Convolutional neural network architecture.*

5. EXPERIMENTS

5.1. Data

Over 3000 path gain measurements were collected in Fuerteventura, Canary Islands, characterized by variable terrain with dry volcanic soil, mostly devoid of vegetation. The measurement consisted of placing an omnidirectional transmit antenna at 4 m above local terrain, emitting a 20W tone at 1.8 GHz. Measurements of received power were collected using an omnidirectional receive antenna at 1 m above ground, towed behind a vehicle. Care was taken to avoid signal blockage by the vehicle itself. Receive power was averaged over several meters to reduce the effect of small scale fading and corresponding path gain was computed as the difference in dB between receive and transmit power, after compensating for vertical antenna gains. Data was collected at ranges from 20 m to 4 km, with over 10 dB SNR, for measurement fidelity.

Figure 4 illustrates the terrain where measurements were taken. The white circle points the transmitter location.

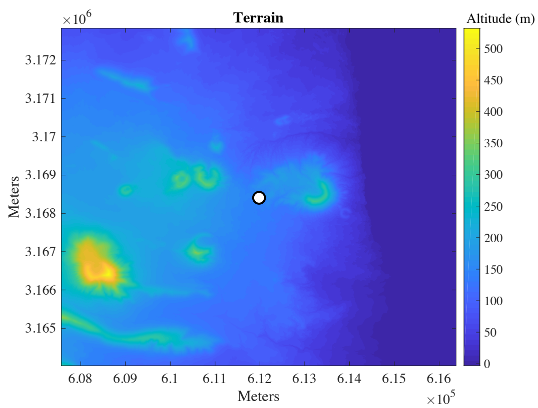

Fig. 4. *Terrain map. The white circle indicates transmitter location.*

5.2. Implementation

All models were implemented in python using `Keras` library [22] with tensorflow [23] backend. Models were trained using Adam optimizer [24] for 300 epochs using mini batch training with batch size 32 on a regular CPU laptop. Code can be found online at `https://github.com/mriberodiaz/path_loss`

5.3. Model exploration and results

We trained several architectures for two different approaches. First, feed forward networks that consist only of fully connected layers, varying number of layers and neurons based on a sensitivity analysis and cross validation. Second, we trained different architectures that included one or more convolutional and pooling layers preceding a fully connected network. We report only the best model for each approach. We used cross validation over 5 folds to select the best model. Path loss is measured in dB to have a consistent scale that captures the large range of values.

We compare against a slope-intercept model of the measurements. The slope-intercept uses least squares to find the best linear fit to path gain in terms of distance. Figure 6 shows the real measurements as a function of distance in meters and the linear fit. From this plot we observe that a slope-intercept model, as it depends only on distance between receiver and transmitter, cannot describe signal strength variations, due to terrain features.

Table 1 shows the RMSE and the standard deviation in the log scale for the slope intercept model and the mean performance of the best feed forward and convolutional networks over a 5 fold cross validation scheme. For the slope-intercept model, we report the average over all data set as it does not require training. Results show that both the feed forward network and convolutional network have better performance than the slope-intercept model. Moreover, the convolutional network outperforms the feed forward network by almost 2 dB.

In Table 1 we also show the standard deviation of error predictions across folds. We observe that both neural networks have a small variance. Besides the small error, the small variance is also evidence of both models' generalization. We leave for future work to test how well neural networks generalize to new terrains and not only to new terrain profiles from a same area.

Table 2 shows that the number of parameters is high for deep learning models due to the high dimensional input vector (736). However, training time is very short and does not require a GPU. Furthermore, for deployment, only model evaluation is needed and evaluating the networks is even faster, taking miliseconds to compute one prediction. And despite the large number of parameters, the crossvalidation results, RMSE and standard deviation, evidence that the model is not overfitting and generalizes well.

Model	**RMSE (dB)**	Standard deviation (dB)
Slope-intercept of terrain profile	12.7	–
Feed forward neural network	6.7	0.18
Convolutional neural network	4.9	0.20

Table 1. Model performance

Model	**Training time (min)**	**Number of parameters**
Feed forward neural network	1	197K
Convolutional neural network	6	787K

Table 2. Training time and number of parameters for deep learning models

In Figure 5, in the upper left plot we show the measured path gain over the terrain map for a test set. It can be observed how signal strength is higher closer to the transmitter (you can refer to Figure 4 to compare with the terrain map and transmitter location) and decreases as the receiver moves away. However, it can be observed on the figure that received power does not decrease monotonically with increasing range. This is because of all the effects introduced by terrain irregularities. On the upper right we plot the predictions for the same measurements using the slope-intercept fit. On the bottom left we plot the convolution network predictions and on the bottom right we plot the feed forward network predictions. The plotted measurements are on test data, not used during the networks' training.

Figure 5 shows that deep learning models are able to capture signal strength variation across all the terrain. Comparing against the terrain, it can be observed that the model makes accurate predictions for different profiles. In contrast, the slope-intercept model under-predicts near the transmitter and over predicts in other areas.

Finally, Figure 7 shows cumulative distribution of errors for the three models. The plot confirms that both Deep Learning models have lower errors than the slope-intercept fit.

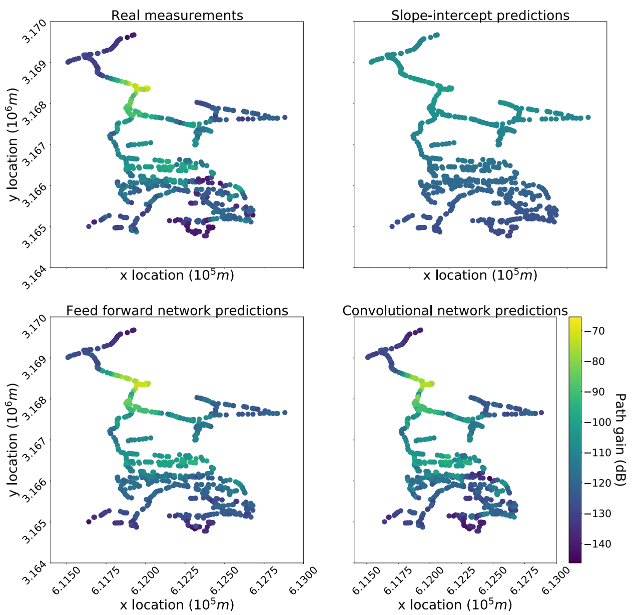

Fig. 5. *Measurements and predictions over terrain map using different models. Color intensity represents path gain in dB, measured and predicted respectively. The upper left plot shows the path loss intensity of real measurements. The upper right, the predicted path gain using the slope intercept fit. The bottom plots show the predictions using deep learning models (feed forward on the left and convolutional on the right). Deep learning models are able to predict path loss accurately across the whole terrain,*

Our results are an empirical evaluation showing that deep learning models can greatly improve empirical propagation models in terms of accuracy. Our proposed approach captures variations in path loss variations that depend not only on the distance between transmitter and receiver but on terrain elevation variations. Furthermore, they are computationally less expensive than deterministic models.

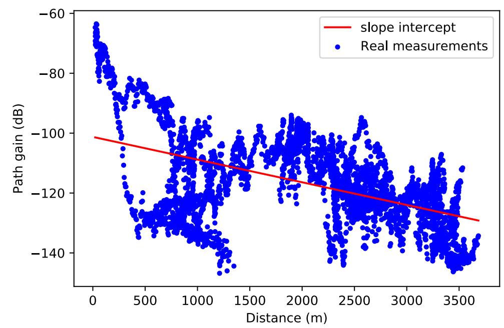

Fig. 6. *Slope-intercept model. Real measurements as a function of distance are plotted in blue. Traditional slope-intercept models do not describe accurately path gain using a linear fit.*

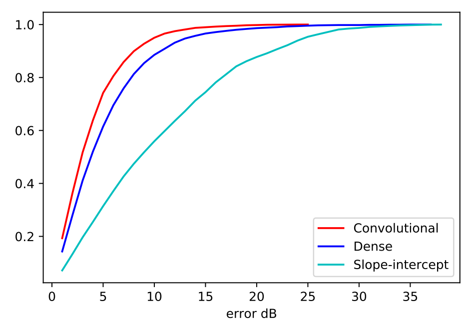

Fig. 7. *Cumulative distribution of errors for all different models*

6. CONCLUSIONS

We present a novel deep learning propagation model for settings with irregular terrain. Current solutions are based on extensive measurements campaigns that fit slope-intercepts to the data resulting in very high RMSE. Our framework and set of features exploit the environment and demonstrate the potential of deep learning to accurately predict path gain. Our results show an 8 dB improvement comparing with a traditional empirical model that fits a slope-intercept model.

We present evidence that our models generalizes to new profiles on the terrain map. This question could be studied with a larger data set for different terrain maps for environments with similar conditions. Future work and improvements also includes working with wider terrain sections to account for lateral scattering. One advantage of deep learning models is their ability to receive inputs with two or more dimensions. Adding wider terrain areas could improve models' accuracy at the cost of computing power as more parameters have to be optimized.

Finally, this framework can be extended to different scenarios to model propagation over more complicated settings involving terrestrial clutter, e.g. vegetation, buildings, etc. We plan to explore that in future work.

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