Physics-embedded machine learning method for the prediction of long-range electromagnetic field propagation

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Abstract: We propose a sequential physics-embedded machine learning method to predict propagation over rural terrain. The training process uses artificial data computed by solving the parabolic wave equation. A fine-tuning strategy is also proposed, rendering the method versatile. Numerical simulations are provided to validate the proposed approach.

Fast and accurate computational methods are necessary to model the tropospheric electromagnetic long-range propagation to predict, for example, the coverage of antenna systems, such as for 5G applications. In this context, numerous physical phenomena such as *the terrain* shall be considered

For such applications, the *knife-edge model* [1] is widely used since it allows a first estimation in almost real-time, but its accuracy is low when real-life reliefs are studied. For better prediction, can based on the accelerated surface integral equation [2], the ray tracing method [3], or the *parabolic wave equation model* (PWE) [4,5]. Indeed, they trade computational time for better accuracy. This is why *machine learning* methods have recently received a lot more attention from the community; see [6] for an overview. In particular, in [7] they proposed a U-Net-based architecture trained from artificial data computed using a ray-tracing method. The latter model allows good predictions in almost real-time for indoor propagation. Based on the same architecture, Brennan *et al.* [8] proposed a machine-learning model to predict the long-range propagation over rural terrain. Nonetheless, this method uses data that resemble rural terrains, which leads to good results when the relief has a similar shape.

In this work, we propose to use the same architecture, *i.e.*, a U-Net, because it has shown good results in the domain. However, we propose a different training method that proves to be more versatile. Indeed, artificially labeled training data are created using the PWE model solved with split-step wavelet [5], which allows one to account for the terrain through a staircase model [4]. With that physical *a priori* we propose to construct a data set with rectangular and triangular obstacles placed randomly in the domain using a *Latin Hypercube Sampling* (LHS) method to precisely sample the associated manifold. We used 4000 terrain samples that contain between 2 and 5 random obstacles of different sizes. It shall be noted that the set is equidistributed and that this construction method is completely generalizable to add the effect of ground composition or refraction for example. The proposed U-Net architecture, with 4 levels of encoding and decoding, is then trained with a proper loss function, i.e., a weighted combination of an L2 and L1 norm, using 80% of the dataset. The other 20% are used as test dataset. The trained predictor allows us to obtain good results on the validation dataset, consisting of terrain with 6 random obstacles, and even on real-life terrain data obtained with the IGN dataset [9]. Nonetheless, for very specific applications, such as propagation over the sea, the terrain can be very different, and the predictor accuracy reduces drastically. Therefore, to render the method versatile, we propose a *fine-tuning strategy,* where only the decoding layers are trained again with a reduced dataset that resembles the studied terrain to improve the accuracy and adapt the predictor for the desired application. To the author’s knowledge, this strategy has not yet been proposed for tropospheric propagation.

To conclude this summary, we present two simulations in Figures 1 and 2. First, the proposed machine-learning method is used to predict the propagation between Paris and Chartres accounting for the real terrain, and shows very good results, since the overall behavior of the field is well retrieved. Furthermore, the prediction is performed in almost real-time, with a computation time below 0.07 s. It thus allows a first glance at the field propagation with better accuracy than a conventional knife-edge model. Second, the advantage of the fine-tuning strategy is shown when a random Gaussian terrain is accounted for. Indeed, it allows to drastically improve the accuracy of the prediction. In both cases, we show the mean square error (MSE) in the legend. One can note that for the IGN landscape, we have an MSE of 1.01, which is low considering 4000 samples of very general terrain are used for the training. In the second case, we can note that the error has been divided by more than 6 using the fine-tuning strategy with 1500 samples of Gaussian terrain.

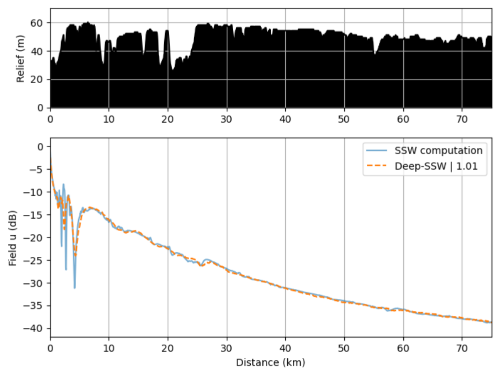

Figure 1: Prediction of the field (dB) over a real landscape.

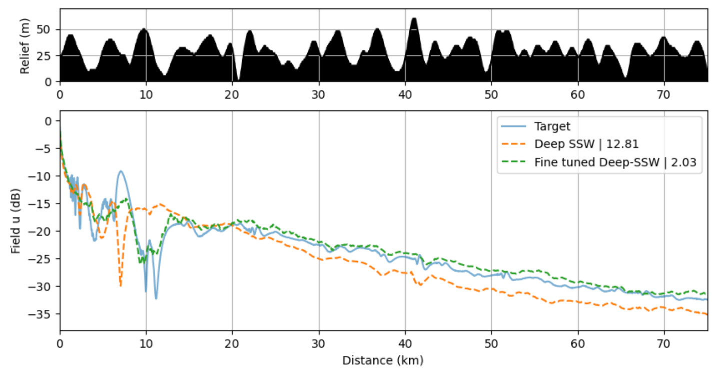

Figure 2: Prediction of the field (dB) over a Gaussian terrain.

In the full version of the article, a thorough study of the error with the number of samples and the fine-tuning strategy will be proposed.

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