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Deep learning based higher-order approximation for multiple knife edge diffraction

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***Abstract*—We introduce an hybrid approach for computing multiple knife-edge diffraction attenuation. First, we show that the well-known Epstein-Peterson method can be considered as the first order approximation of the Vogler method. In the other words, the Vogler method is a combination of the Epstein-Peterson method and an higher order approximation. Then, we propose to learn the approximation based on deep learning methods. The key advantage of this approach is the significant reduction of generating training data to approximate the Vogler method while still offering a good accuracy and fast computation. Comparison to the state-of-the-art methods demonstrates the effectiveness of our proposed approach.**

I. Introduction

Estimation of diffraction loss from propagation of radio waves over obstacles modeled by multiple knife edges is an important problem in wireless channel modeling, radio coverage prediction, to name a few [1].

Many approaches have been proposed to deal with this crucial problem, ranging from accurate and computational intensive methods to geometrical construction based trade-off ones [1]. The fundamentals behind those approaches are based on physics with rigorous theories. The Vogler [2] is one of the best methods in terms of accuracy, supported by both theoretical analysis and practical measurements [1]. However, it is slow due to the high computational cost.

In the past few years, there has been a surge in methods based on machine learning, particularly deep learning (DL), for this problem. This growth is inspired by many empirical successes in, for example, natural language processing and computer vision [3]. The high capacity in modeling complicated processes creates an attractive constituent of this approach. The requirement of large data and long training time, however, are always posing a challenge to use DL in practice.

In [4], we proposed a deep neural network, known as VoglerNet, to obtain an accurate estimation of the diffraction values, where the training data are generated from the Vogler method. Still, VoglerNet requires large training data to reach a desired accuracy. Our objective here is to exploit the modeling knowledge to reduce the amount of training data and, hence, training time. To this end, we first show that the graphic based Epstein-Peterson (E-P) method [5] can be regarded as the first order approximation of the Vogler method. By using the E-P as a baseline approximation, we then can learn the higher order approximation by a deep neural network (DNN) with much less training data while preserving the adequate accuracy and being a fast solution.

II. Multiple knife edge diffraction

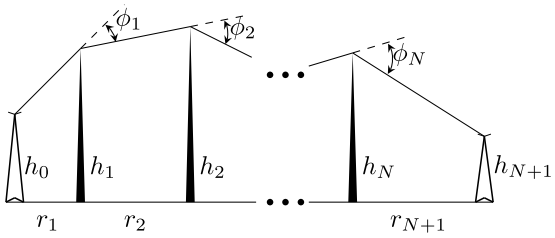

Fig. 1: Geometry of multiple knife edges.

The geometry of N knife-edge diffraction is presented in Fig. 1, where $\{h_n\}_{n=1}^{N}$ are the knife-edge heights to a reference surface, $\{\phi_n\}_{n=1}^{N}$ are diffraction angles, and $\{r_n\}_{n=1}^{N+1}$ are $N+1$ separation distances between knife-edges. Moreover, h_0 and h_{N+1} denote the transmitter and receiver heights respectively. To illustrate the key ideas, we will consider the case of $N = 3$ herein. The E-P method calculates a diffraction attenuation by examining each knife edge as a source for the next one [5]:

$$A_{\text{EP},3} = \frac{(1+j)^3}{2^3} \prod_{i=1}^{3} \int_{v_i}^{\infty} \exp\left(-j\frac{\pi}{2}x_i^2\right) dx_i \tag{1}$$

where $v_i = \phi_i \sqrt{\frac{2r_i r_{i+1}}{\lambda(r_i + r_{i+1})}}$ with j and λ referring to imaginary number and wavelength respectively. In a similar but more accurate way, the diffraction attenuation is given by Vogler method as follows [2]:

$$A_{\text{V},3} = \frac{1}{\left(\sqrt{\pi}\right)^3} C_3 \exp(\sigma_3) \sum_{m=0}^{\infty} \frac{2^m}{m!} \times \int_{\beta_1}^{\infty} \int_{\beta_2}^{\infty} \int_{\beta_3}^{\infty} g^m \exp\left(-\left(u_1^2 + u_2^2 + u_3^2\right)\right) du_1 du_2 du_3 \tag{2}$$

where

$$C_3 = \sqrt{\frac{r_2 r_3 (r_1 + r_2 + r_3 + r_4)}{(r_1 + r_2)(r_2 + r_3)(r_3 + r_4)}}, \tag{3}$$

$$\sigma_3 = \beta_1^2 + \beta_2^2 + \beta_3^2, \tag{4}$$

$$g = \phi_1 (u_1 - \beta_1)(u_2 - \beta_2) + \phi_2 (u_2 - \beta_2)(u_3 - \beta_3), \tag{5}$$

$$\beta_n = \phi_n \sqrt{\frac{jkr_n r_{n+1}}{2(r_n + r_{n+1})}}, \quad \text{where } 1 \le n \le 3, \tag{6}$$

and $k = 2\pi/\lambda$. If $m = 0$, we can simplify (2) as follows:

$$A_{V,3} = \frac{1}{(\sqrt{\pi})^3} C_3 \exp(\sigma_3) \prod_{i=1}^{3} \int_{\beta_i}^{\infty} \exp\left(-x_i^2\right) dx_i. \quad (7)$$

III. Proposed Approach

We first present the following lemma that describes the relation between the Vogler and E-P methods. Then, inspired by this connection, we propose to use a DL approach to approximate higher-order terms that represent a non-linear difference between attenuation values computed by the two methods. More specifically, we use a *multilayer cascade-forwad neural network* (CFNN), instead of a feed-forward NN (FFNN) as in [4], for this approximation task.

Lemma 1: Given the small angle assumption, that is, $\sin(\phi_i) \simeq \phi_i$ and $\phi_i > 0$, for $i = 1, \ldots, N$, the Epstein-Peterson method is a first order approximation of the Vogler method, up to the scaling factor C_N. In the other words,

$$A_{\mathrm{V}} \approx C_N A_{\mathrm{EP}} + O(m) \quad (8)$$

where $O(m), m \geq 1$, refers to the higher order approximation of the Vogler method.

Proof: By making the change of variable $u = \sqrt{\frac{j\pi}{2}} x$, for $i = 1, \cdots, N$, we have

$$\int_{\beta_i}^{\infty} \exp\left(-u^2\right) du = \sqrt{\frac{j\pi}{2}} \int_{\nu_i}^{\infty} \exp\left(-j\frac{\pi}{2}x^2\right) dx. \quad (9)$$

Then it is straightforward to reach the result (i.e., we can convert between (1) and (7)). ■

Lemma 1 shows that, by comparing to the first order approximation of the Vogler method, the E-P method underestimates the diffraction attenuation loss by a factor of $20\log(C_N)$ [dB].

Motivated by this lemma, we propose to learn the non-linear higher-order terms by a DNN as presented in Fig. 2. In the training stage, a DNN is used to approximate the difference between the Vogler and E-P method using the corrected factor. Then, in the testing stage, this approximation helps complement the results from the E-P method that provides a 'rough' estimate. Thus, we can reduce the training data significantly while retaining a good accuracy. We choose a CFNN architecture that is similar to FFNN but includes a connection from the input and every previous layer to following layers. Parameters of the CFNN are obtained by minimizing a loss function by the Levenberg-Marquardt backpropagation with a Bayesian regularization [4]. The loss function includes empirical risk and Tikhonov regularization terms, aiming to optimal to the given training dataset and to bypass overfiting problem [3].

IV. Simulation Results

To illustrate the effectiveness of the proposed approach, we used a test with $N = 3$. For a quantitative assessment, path profiles including the heights of knife edges and their separation distances were generated randomly in the range of (0,1) and (1,10) km, respectively. Their corresponding diffraction values were obtained by using Vogler algorithm.

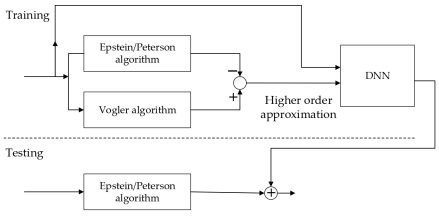

Fig. 2: Illustration of proposed system.

Moreover, the dataset was randomly split into training (80%) and test (20%) sets. The mean squared error (MSE) was used as a performance metric. For qualitative assessment, we verified the results with an example as described in [2] and [4] (see Fig. 3) where the middle knife-edge (i.e., h_2) with variable height increasing from 0 to 0.8 km. The diffraction attenuation curve, thus, coincides with that of the single knife-edge. We can observe that, the proposed method resulted in has smaller MSE (see Table I) and produced better curve trend than other methods (see Fig. 3). Here, we obtain a similar result with a dataset of 50.000 samples, 10 times smaller than 500.000 samples used in [4] (i.e., in terms of qualitative assessment).

TABLE I: MSE-based error comparison of four algorithms for a dataset of 50.000 samples.

Methods	Proposed meth.	VoglerNet	E-P meth.	Shallow NN
MSE (dB)	**1.38**	2.26	695.88	10.98

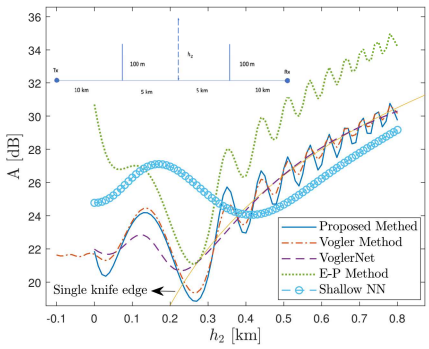

Fig. 3: Qualitative assessment of four different methods.

V. Conclusion

We have proposed a hybrid method to solve multiple knife diffraction problem. By approximating higher-order terms by a deep cascade-forward neural network in the training phase and using this approximation to enhance the accuracy in the test phase, we reached a similar accuracy as using larger dataset.

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