Machine Learning Based Approach for Diffraction Loss Variation Prediction by the Human Body

Mohsen Khalily, *Senior Member, IEEE*, Tim W. C. Brown, *Member, IEEE*, Rahim Tafazolli, *Senior Member, IEEE*

Abstract—This paper presents a machine learning (ML) based model to predict the diffraction loss around the human body. Practically, it is not reasonable to measure the diffraction loss changes for all possible body rotation angles, builds and line of sight (LoS) elevation angles. A diffraction loss variation prediction model based on a non-parametric learning technique called Gaussian process (GP) is introduced. Analysed results state that 86% correlation and normalised mean square error (NMSE) of 0.3 on the test data is achieved using only 40% of measured data. This allows a 60% reduction in required measurements in order to achieve a well-fitted ML loss prediction model. It also confirms the model generalizability for non-measured rotation angles.

Index Terms—Diffraction loss, gaussian process (GP), machine learning (ML), network planning tool.

I. INTRODUCTION

MACHINE learning (ML) techniques have found applications in many research areas including engineering and biomedical applications [1]–[5]. Recently, several studies have also employed ML methods for signal propagation prediction and antenna design applications.

A support vector machine (SVM) is a supervised technique based on optimising a hyperplane that best separates data points from two different classes. The data can be classified either in the original space or by transferring the data into a kernel space that may make the data more separable. SVMs with two linear and non-linear kernels have been considered for scintillation events classification [6]. The data from Peru, Ascension Island and Hong Kong was used for training the ML classifier while the model was tested on a dataset from Singapore. In another work, a classification and regression tree (CART) was used for predicting scintillation events [7]. CART is a tree based method in which a feature is selected at each stage to best split the data.

In addition to scintillation prediction, there are a few ML studies on antenna design parameter prediction [8], [9]. Tak et al. used a neural network based on the Multi-layer perception (MLP) model to learn the design parameters (orientation angles and length of coupling slots) [8]. Seven design parameters and the sum of S_{11} were considered as the input and output of a MLP network with only one hidden layer of 10 nodes. Although a neural network normally needs more data for the training, only 189 samples were collected in their study. A neural network with Bayesian regularisation was employed

Fig. 1. Diffraction measurement setup.

for design space prediction in [9]. In their work, ML was used to map the parameters of the nano-magnetic material to antenna characteristics. However, similarly a limited number of data samples was generated and used in their training phase. Furthermore, ML has found application to Multiple-input multiple-output (MIMO) channel estimation based on minimum normalised mean square error [10], maximum likelihood [11] and SVM [12].

This paper presents a machine learning based approach to support modelling of diffraction loss around a human body at mmWave frequencies. Models such as the double knife edge [13], geometric theory of diffraction [14] or more recent work by the authors on the shield edge [15] could be equally applied to obtain a predicted diffraction loss based on the width of the body. However, this will only model one part of the loss around a body that can be found deterministically. A body is an irregular structure unlike a flat straight edged plate of conductor assumed in such models. The irregular structure together with body movements will cause variation in the diffraction resulting in an additional fading loss that is modelled stochastically based on empirical results. Measurements have shown that this fading has a Gaussian distribution [16]. Frontal and lateral diffraction loss by one to three human bodies moving along a transmit to receive path were considered and its alignment with Voglers multiple knife-edge model were shown in [17]. To obtain conclusive empirical results of the mean and standard deviation requires extensive measurements on different size human bodies and positions. Such extensive measurements on a single body and extending to multiple subjects are not manageable, which demands the need for a machine learning algorithm to accurately predict the statistics based on a smaller manageable number of measurements as

M.Khalily, T.W.C Brown, and R.Tafazolli are with the Institute for Communication Systems (ICS), Home of the 5G Innovation Center (5GIC), University of Surrey, Guildford, UK. (e-mails: {m.khalily, t.brown, r.tafazolli@surrey.ac.uk}).

a training sequence. This paper demonstrates the capability of machine learning to do this task, based on comparison with measured results at 10-12 GHz. The results in this paper accurately predict both the first and second order statistics of fading by a human body obstructing a line of sight with varying azimuthal rotations.

II. MEASUREMENT SCENARIO

The measurement scenario was setup in the manner shown in Fig. 1 whereby the diffraction loss around a human body was measured halfway between a transmitter (Tx) and receiver (Rx) separated 3 m apart and in the frequency range 10-12 GHz. For this study, it was only necessary to have a Fresnel zone that was comparable with the width of the body and 10-12 GHz was chosen as a suitable frequency range. The method could still be applied to higher frequencies where the same criteria is still true, it would not be the case with much lower frequencies as the Fresnel zone would get wider. Directional antennas were used with a non negligible Rayleigh distance, which will have increased the diffraction loss compared to using omnidirectional antennas [3] though this effect is not of concern in this work. There are a number of physical parameters shown in Fig. 1 that would demand extensive measurements to obtain empirical results on the fading. Two angles are defined as the elevation of the line of sight, θ_{LOS} and the azimuth rotation of the body, θ_{BODY} . The shield edge Fresnel diffraction parameters u and v defined in [3] based on the width of the body and its offset from the line of sight respectively will also affect the diffraction. To prove the concept in this paper, θ_{LOS} and w are fixed at zero, while u is a constant value of 2.35 at the center frequency across the torso shown in Fig. 2 when the body is facing the Tx. The one variable used in this work is the azimuth rotation of the body, θ_{BODY} from here onwards abbreviated to θ . Body gestures and build are other factors affecting the diffraction demanding more measurements but just one human body standing with arms down is assumed here. There will be a variation in diffraction loss as the body rotates that is a maximum when $\theta = 0^\circ$ or 180° and minimum when $\theta = 90^\circ$ or 270° . Ten measurements from 0° to 360° in 45° steps were undertaken. We should note that due to the random structure of the body and that it will not have the arms or clothing in exactly the same position when it has rotated from 0° to 360° , then the losses will not be exactly the same. By virtue of the body's irregular shape, each of the ten measurements were not repeatable and subject to different fading. Therefore extensive measurements, or predictions from machine learning are required for obtaining an empirical result to model the mean and standard deviation of the Gaussian fading studied in this work due to body rotation.

III. DIFFRACTION LOSS PREDICTION METHOD

A. Background

In a machine learning context, supervised learning refers to predicting outputs of unseen inputs. The prediction model is learned based on the observed data. It is while the problem for a continuous data is called regression. Traditionally,

Fig. 2. Body diffraction loss measurement.

regression problems are solved with parametric techniques in which a model is considered and its parameters learned from the observed training data. Several linear and non-linear techniques exist mainly based on the least square method to fit a function on the data. The main disadvantage of all these techniques is that they are based on some assumption regarding the data and the model smoothness. A Gaussian Processes is a supervised non-parametric method that can learn noise and uncertainty by considering a probability distribution over all possible functions [18].

B. Machine Learning Approach

There is a difference between Gaussian process (GP) and Gaussian distribution (GD). GD is a bell shaped probability distribution that is defined by a mean and covariance ($\mathcal{N}(\mu, \sigma)$). GP is a GD generalisation to infinite variables and defined by a mean function $m(\mathbf{x})$ and covariance function $k(\mathbf{x}, \mathbf{x}')$:

$$g(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}')) \quad (1)$$

where x and x' are two data points.

If there is no prior information of the data, the mean function usually is considered as zero. The covariance function on the other hand can be considered as any function that takes two parameters and returns a non-negative definitive covariance matrix. There are several possible functions that can be considered as the covariance function. For instance, a radial basis function (RBF) for the covariance function is defined as:

$$k(\mathbf{x}, \mathbf{x}') = \sigma^2 \exp(-1/(2l^2)|\mathbf{x} - \mathbf{x}'|^2) \quad (2)$$

where l is the length scale parameter. As seen in the RBF formulation, the covariance between two inputs is close to one if two inputs are close to each other. Parameters can significantly impact the performance of the GP model.

Considering a number of inputs and their corresponding observations as $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N\}$ and $\{y_1, y_2, \dots, y_N\}$ respectively, the aim is to predict the observations for a new unseen data input.

The input data matrix is shown by $\mathbf{X}$ and the test points or points we would like to estimate as $\mathbf{X}^*$. If we assume that each observation is a sample from a GP, it can be represented as

$$y = g(\mathbf{x}) + \epsilon \quad (3)$$

Fig. 3. GP diffraction loss estimation for $\theta = \{0, 1, 2, \dots, 360\}$ and $f = 12$ GHz. The estimated diffraction loss is represented for 1, 4, and 9 training measured data compared with the measured test data for two different scenarios (a) test data is #10 and the rest are training data, (b) test data is #5 and the rest are training data.

in which ϵ represents the Gaussian white noise. Considering GP as a number of variables with GD, the problem of estimating a observation for each input $\mathbf{x}^*$ can be represented as:

$$\begin{bmatrix} \mathbf{y} \\ \mathbf{y}^* \end{bmatrix} \sim \mathcal{N}\left(0, \begin{pmatrix} \mathbf{k}(\mathbf{X}, \mathbf{X}) + \sigma_n^2 \mathbf{I} & \mathbf{k}(\mathbf{X}, \mathbf{X}^*) \\ \mathbf{k}(\mathbf{X}^*, \mathbf{X}) & \mathbf{k}(\mathbf{X}^*, \mathbf{X}^*) \end{pmatrix}\right) \quad (4)$$

Different covariance matrices can be used. In this study by considering noisy measurements, the covariance matrix was considered as:

$$\text{cov}(y_p, y_q) = \mathbf{k}(\mathbf{x}_p, \mathbf{x}_q) + \sigma_n^2 \delta_{pq} \quad (5)$$

where $\mathbf{k}$ is defined in Eq. (2). δ is the Kronecker delta as a function of two variables and is equal to 1 if its variables are equal.

In order to estimate y^* , the mean and variance must be estimated. Based on Eq. (4), the aim is to estimate the conditional distribution of y^* given y . Both variables are jointly Gaussian and hence we can write the conditional estimation as:

$$\begin{aligned} y^* | y &\sim \mathcal{N}(\bar{\mathbf{g}}^*, \text{cov}(\mathbf{g}^*)) \\ \bar{\mathbf{g}}^* &= \mathbf{k}(\mathbf{X}, \mathbf{X}^*)^T \mathbf{C}^{-1} \mathbf{y} \\ \text{cov}(\mathbf{g}^*) &= \mathbf{k}(\mathbf{X}^*, \mathbf{X}^*) - \mathbf{k}(\mathbf{X}, \mathbf{X}^*)^T \mathbf{C}^{-1} \mathbf{k}(\mathbf{X}, \mathbf{X}^*) \\ \mathbf{C} &= \mathbf{k}(\mathbf{X}, \mathbf{X}) + \sigma_n^2 \mathbf{I} \end{aligned} \quad (6)$$

where $\mathbf{I}$ is the identity matrix. $\bar{\mathbf{g}}^*$ represents the regression coefficients and returns the best estimation of y^* . $\text{cov}(\mathbf{g}^*)$ indicates the estimation uncertainty and only depends on input variables. The marginal likelihood ($p(y|\mathbf{X})$) is then defined as:

$$p(y|\mathbf{X}) = \int p(y|g, \mathbf{X}) p(g|\mathbf{X}) dg \quad (7)$$

By considering that the likelihood is Gaussian, the logarithmic marginal likelihood can be written as:

$$\log p(y|\mathbf{X}) = 1/2 \mathbf{y}^T \mathbf{C}^{-1} \mathbf{y} - 1/2 \log |\mathbf{C}| - n/2 \log 2\pi \quad (8)$$

The first part includes only the past observations (diffraction loss). Second term depends only on the covariance function as a regularisation term and the last term is only a constant normalisation term.

C. Model and Results

In this study, each measurement is a vector of two frequencies, f , and rotation angles, θ , and is represented as $\mathbf{x}_i = \begin{bmatrix} f_i \\ \theta_i \end{bmatrix}$. Hence, considering a number of measurements and their corresponding measured diffraction loss as $\begin{bmatrix} f_1 \\ \theta_1 \end{bmatrix}$, $\begin{bmatrix} f_2 \\ \theta_2 \end{bmatrix}$, ..., $\begin{bmatrix} f_N \\ \theta_N \end{bmatrix}$ and $\{l_{\text{diff}1}, l_{\text{diff}2}, \dots, l_{\text{diff}N}\}$ respectively, the aim is to estimate the loss function for a new measurement. Consequently the covariance matrix in Eq. (5) can be rewritten as:

$$\text{cov}(l_{\text{diff}p}, l_{\text{diff}q}) = \mathbf{k}\left(\begin{bmatrix} f_p \\ \theta_p \end{bmatrix}, \begin{bmatrix} f_q \\ \theta_q \end{bmatrix}\right) + \sigma_n^2 \delta_{pq} \quad (9)$$

where $\mathbf{k}$ is the RBF function, $\mathbf{k}\left(\begin{bmatrix} f \\ \theta \end{bmatrix}\right) = \sigma^2 \exp(-1/(2l^2) \left| \begin{bmatrix} f \\ \theta \end{bmatrix} - \begin{bmatrix} f \\ \theta \end{bmatrix}' \right|^2)$. Consequently, the regression coefficients and the estimation uncertainty in Eq. (6) is represented as below in our setting:

$$\begin{aligned} l_{\text{diff}}^* | l_{\text{diff}} &\sim \mathcal{N}(\bar{\mathbf{g}}^*, \text{cov}(\mathbf{g}^*)) \\ \bar{\mathbf{g}}^* &= \mathbf{k}\left(\begin{bmatrix} \mathbf{F} \\ \Theta \end{bmatrix}, \begin{bmatrix} \mathbf{F} \\ \Theta \end{bmatrix}^*\right)^T \mathbf{C}^{-1} l_{\text{diff}} \\ \text{cov}(\mathbf{g}^*) &= \mathbf{k}\left(\begin{bmatrix} \mathbf{F} \\ \Theta \end{bmatrix}^*, \begin{bmatrix} \mathbf{F} \\ \Theta \end{bmatrix}^*\right) - \mathbf{k}\left(\begin{bmatrix} \mathbf{F} \\ \Theta \end{bmatrix}, \begin{bmatrix} \mathbf{F} \\ \Theta \end{bmatrix}^*\right)^T \mathbf{C}^{-1} \mathbf{k}\left(\begin{bmatrix} \mathbf{F} \\ \Theta \end{bmatrix}, \begin{bmatrix} \mathbf{F} \\ \Theta \end{bmatrix}^*\right) \\ \mathbf{C} &= \mathbf{k}\left(\begin{bmatrix} \mathbf{F} \\ \Theta \end{bmatrix}, \begin{bmatrix} \mathbf{F} \\ \Theta \end{bmatrix}\right) + \sigma_n^2 \mathbf{I} \end{aligned} \quad (10)$$

where $\mathbf{F}$ represents the matrix of frequencies and Θ is the matrix of rotation angles.

In this work, diffraction loss was measured for the frequency range of $\{10 \text{ GHz}, 10.02 \text{ GHz}, 10.04 \text{ GHz} \dots, 12 \text{ GHz}\}$ and $\theta = \{0, 45, 90, \dots, 360\}$. For each frequency and theta, the measurements were repeated 10 times. Up to 12231 measurement samples (151 frequencies $\times$ 9 measurements $\times$ 9 θ values) in steps of one measurement set containing 1359 measurement samples (151 frequencies $\times$ 9 angle values) were considered as the training data. The remaining 10th measurement step also

Fig. 4. (a) Correlation and (b) NSME between the test measured data and GP estimated values for the test data considering up to 9 measurements for training for 3 different scenarios.

with 1359 measurement samples was reserved for validation purposes. The parameters of the covariance matrix were optimized by an internal cross validation on the training data ($\sigma = 1.41$, $l = 0.5$ with length scale bound = [16.5,17], and $\sigma_n = 1$). The normalised mean squared error (NMSE) on the test data was 0.21. In order to show the advantage of GP in comparison with existing regression techniques, support vector regression (SVR) method with RBF kernel and also polynomial regression (PR) were considered here. Multiple parameter settings have been tried for both techniques and the best NMSE on the test set for SVR and PR were 0.34 and 0.29 respectively confirming the better performance of GP for diffraction loss prediction. The trained model then was used to estimate the diffraction loss function for a frequency value and $\theta = \{0, 1, 2, \dots, 360\}$. The estimated pattern for $f = 12$ GHz and 1, 4, and 9 training measured data compared with the measured test data can be seen in Fig. 3 for two different scenarios. In scenario #1 measured data sets from 1 to 9 have been considered for training data and 10th data set has been considered as a test data. In scenario #2 the 5th data set has been considered as a test data and data sets 1 to 4 and 6 - 10 have been considered for training data. As can be seen by including more measurements in the training, the estimated diffraction loss is closer to the measured test data.

As a result, the impact of having a multiple number of measurements for training the model has been analysed. Nine measured data training sets were available and hence the model was trained by up to nine measurements. For each scenario a different measurement has been selected randomly as the test data and up to 9 remaining measurements considered for the training. Fig. 4 (a) shows correlation between the estimated loss and the true values on the test data for three different scenarios. In scenario #3 the first data set has been considered as a test data and data sets 2 to 10 have been considered for training data. It is seen increasing the number of measurements for training the model results in a higher correlation between the estimated values and the measured test data. Similarly, NMSE values were reported in Fig. 4 (b) for the estimated diffraction loss on the test data indicating more training measurements causing a reduction in the NMSE

values. Results using the proposed ML-based method indicate that to achieve an acceptable estimation, only four, or 40% of the measurements are required as training data. Fig. 4 confirms this whereby four measurements were enough to have an acceptable correlation over 85% and NMSE less than 0.33 or one third. The accuracy is compared in Figs. 3 (a) and (b) where in all scenarios, the curves using 4 and 9 measurements are within 2 dB difference beyond 90° , otherwise within 5 dB. Based on the successful trained model using 40% of measurements as trained data, this can allow a combination of trained and measured data, or just trained data by itself when enough iterations are produced, to create the remaining data that would have been produced by the remaining 60% of measurements. Data representing additional measurements could also be produced as well as characterising the variation at angles in between. Finally, in order to show that GP can perform well even with different test and train configurations, The model was trained; each with measured diffraction loss at all except one of $\theta = \{0, 45, 90, \dots, 360\}$ that was used for testing the model. The average NMSE for the test data was 0.17 showing GP can also perform well for non-similar measurements.

IV. CONCLUSION

A machine learning based model is presented to estimate the variation in diffraction loss around the human body as it rotates. Diffraction loss at mmWave frequencies is an important parameter to consider to calculate path loss. Instead of extensive measurements, a GP method has been deployed to find an extra loss due to body blockage in different rotation angles. 40% of the measured data, or four body revolutions in 45° steps was shown to be sufficient to predict the diffraction loss which would avoid the need for multiple measurements of the same kind. This proves the capability of machine learning to minimise the number of measurements required taking the propagation around the body as an example where extensive measurements would not be humanly possible. The method could equally be applied to ascertain the effect off other parameters such as differing line of sight elevation angles, body build and gestures.

REFERENCES

- [1] K. R. Foster, R. Koprowski, and J. D. Skufca, "Machine learning, medical diagnosis, and biomedical engineering research-commentary," *Biomedical engineering online*, vol. 13, no. 1, p. 94, 2014.
- [2] F. Sebastiani, "Machine learning in automated text categorization," *ACM computing surveys (CSUR)*, vol. 34, no. 1, pp. 1–47, 2002.
- [3] T. Song, L. Kuang, L. Han, Y. Wang, and Q. H. Liu, "Inversion of rough surface parameters from sar images using simulation-trained convolutional neural networks," *IEEE Geoscience and Remote Sensing Letters*, vol. 15, no. 7, pp. 1130–1134, 2018.
- [4] H. M. Yao, W. E. Sha, and L. J. Jiang, "Applying convolutional neural networks for the source reconstruction," *Progress In Electromagnetics Research*, vol. 76, pp. 91–99, 2018.
- [5] S. J. Park, B. Bae, J. Kim, and M. Swaminathan, "Application of machine learning for optimization of 3-d integrated circuits and systems," *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, vol. 25, no. 6, pp. 1856–1865, 2017.
- [6] Y. Jiao, J. J. Hall, and Y. T. Morton, "Automatic equatorial gps amplitude scintillation detection using a machine learning algorithm," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 53, no. 1, pp. 405–418, 2017.
- [7] L. Rezende, E. de Paula, S. Stephany, I. Kantor, M. Muella, P. de Siqueira, and K. Correa, "Survey and prediction of the ionospheric scintillation using data mining techniques," *Space Weather*, vol. 8, no. 6, pp. 1–10, 2010.
- [8] J. Tak, A. Kantemur, Y. Sharma, and H. Xin, "A 3-d-printedw-band slotted waveguide array antenna optimized using machine learning," *IEEE Antennas and Wireless Propagation Letters*, vol. 17, no. 11, pp. 2008–2012, 2018.
- [9] C. Gianfagna, H. Yu, M. Swaminathan, R. Pulugurtha, R. Tummala, and G. Antonini, "Machine-learning approach for design of nanomagnetic-based antennas," *Journal of Electronic Materials*, vol. 46, no. 8, pp. 4963–4975, 2017.
- [10] J. Baltersee, G. Fock, and H. Meyr, "Achievable rate of mimo channels with data-aided channel estimation and perfect interleaving," *IEEE Journal on Selected Areas in Communications*, vol. 19, no. 12, pp. 2358–2368, 2001.
- [11] Q. Sun, D. C. Cox, H. C. Huang, and A. Lozano, "Estimation of continuous flat fading mimo channels," in *Wireless Communications and Networking Conference, 2002. WCNC2002. 2002 IEEE*, vol. 1. IEEE, 2002, pp. 189–193.
- [12] M. Sánchez-Fernández, M. de Prado-Cumplido, J. Arenas-García, and F. Pérez-Cruz, "Svm multiregression for nonlinear channel estimation in multiple-input multiple-output systems," *IEEE transactions on signal processing*, vol. 52, no. 8, pp. 2298–2307, 2004.
- [13] M. Jacob, S. Priebe, R. Dickhoff, T. Kleine-Ostmann, T. Schrader, and T. Kurner, "Diffraction in mm and sub-mm wave indoor propagation channels," *IEEE Transactions on Microwave Theory and Techniques*, vol. 60, no. 3, pp. 833–844, 2012.
- [14] W. Qi, J. Huang, J. Sun, Y. Tan, C.-X. Wang, and X. Ge, "Measurements and modeling of human blockage effects for multiple millimeter wave bands," in *2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC)*. IEEE, 2017, pp. 1604–1609.
- [15] T. W. C. Brown and M. Khalily, "Integrated shield edge diffraction model for narrow obstructing objects," *IEEE Transactions on Antennas and Propagation*, vol. 66, no. 12, pp. 6588–6595, 2018.
- [16] P. Karadimas, B. Allen, and P. Smith, "Human body shadowing characterization for 60-ghz indoor short-range wireless links," *IEEE Antennas and Wireless Propagation Letters*, vol. 12, pp. 1650–1653, 2013.
- [17] X. Zhao, Q. Wang, S. Li, S. Geng, M. Wang, S. Sun, and Z. Wen, "Attenuation by human bodies at 26-and 39.5-ghz millimeter wavebands," *IEEE Antennas and Wireless Propagation Letters*, vol. 16, pp. 1229–1232, 2017.
- [18] N. M. Nasrabadi, "Pattern recognition and machine learning," *Journal of electronic imaging*, vol. 16, no. 4, p. 049901, 2007.