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Assessment of EMF Exposure from Urban Sensor Measurements by Using Artificial Neural Network

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Abstract

This paper studies the electromagnetic field (EMF) exposure emitted by base stations (BSs) from cellular networks in the urban city environment. We reconstruct the EMF exposure by using artificial neural network (ANN) based on data measured by sensors. We take consideration of spatial locations of real BSs in 14th district of Paris, time variation and antenna orientation. And most importantly, we propose a new path loss model to capture the Light-of-Sight (LoS) and None-Light-of-Sight (NLoS) effects caused by complicated and varying blockages in urban cities. By applying the ANN, we are able to reconstruct EMF exposure for the locations of interest with R^2 up to 0.767. And we provide results under different splitting percentage of training and testing data.

1 Introduction

The electromagnetic field (EMF) exposure has been a hot issue nowadays, especially with the fast development of wireless communication techniques, e.g. deployment of 5G equipment. The population risk perception linked to the emission of base station (BS) in urban cities become a spreading concern for both telecommunication regulators and citizens. In the present paper, radiofrequency exposure from 4G network is analyzed and reconstructed with the help of artificial neural network (ANN) based on the measurements recorded by sensors installed on the streetlamps, e.g., sensors installed in different cities by Observatoire des Ondes [1] and EXEM [2]. Sensors record the EMF exposure from certain frequencies, and those measurements are used to reconstruct and predict outdoor EMF exposure level.

However, there are several challenges, which prevent us from assessing an accurate spatial map of EMF exposure. Due to the complexity of building structure and material, it is difficult to capture the important features of channel information. Second, in the urban environment, the mobile objects in between transmitter and receiver would play an more important role, e.g., the LoS signal could be totally blocked by a passing-by bus. Furthermore, the usage of cellular network may experience peak and trough usage during different time of a day, which results in the time variation of exposure.

Conventional methods are used to assess EMF exposure of the network, like ray-based simulators [3] and Kriging [4]. While considering the complexity of analysis, ability to deal with high dimension data and accuracy of analysis, the mentioned methods are not feasible to cover all the aspects. Therefore, in the present paper, we present the reconstruction of EMF exposure using ANN approach, which captures important features in simulating network and also gives good over-all performance.

2 System Model

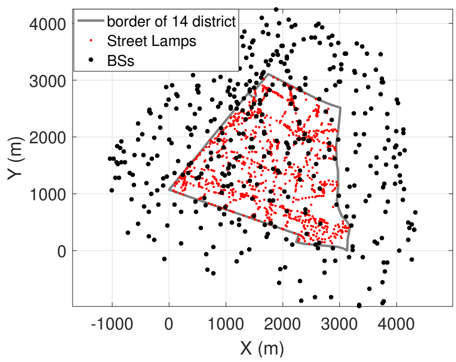

Figure 1. *Map of 14th district in Paris. In total 409 BSs and 3516 streetlamps are displayed in the figure.*

In this paper, a fully-loaded downlink cellular network where BSs operate at 2600 MHz with fixed transmit power is considered. The map of 14th district is shown on the left in Fig 1, with real spatial locations of BSs (from ANFR) and street lamps (possible locations of sensors) are displayed in black and red dots respectively. The directional antenna equipped on each BS has uniformly-distributed orientation of maximum gain. The aggregated exposure perceived by the receiver can be denoted as:

$$P_{exp}(x_j,t) = \sum_{i\in\Phi_{BS}}^{N_{BS}} P_{tx} G_{tx} PL(x_{ij}) f_t(t) \tag{1}$$

where G_{tx} is the gain of transmitting antenna, which depends on the orientation of antenna. $PL(x_{ij})$ is the new block-based path loss attenuation function between receiver x_j and BS_i.

Due to the rapidly changing traffic load, the exposure level can vary significantly at different time in one day, especially in urban cities. This periodical phenomenon can be approximated by using a trigonometric function. Here, $f_t(t) = -0.3sin(t) + 2, 0 \leq t \leq 24$ gives the time variation function in a day, to model the rapidly changing traffic load in urban cities.

To better capture the blockage effect caused by terrain and urban environment. We propose a block-based path loss model, which is defined as:

Proposition 1 *The path loss model is denoted as* $PL = A + 10\alpha(x_j)\log_{10}(d/d_o); d \geq d_o$*, where A is the decibel path loss at distance* d_o*. Here path loss exponent* $\alpha(x_j)$ *is dependent on the location of receiver* x_j*, which is further determined by surrounding blockages around* x_j *in the environment.*

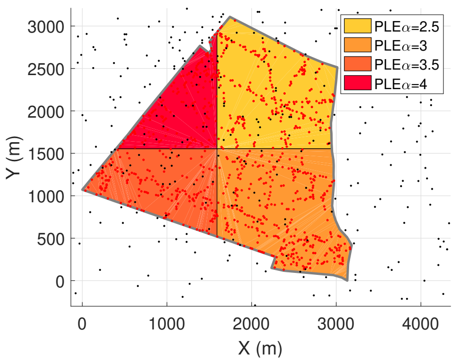

Figure 2. *Block-based path loss model, different colors represent different regions covered by different PLE.*

Proposition 1 indicates different regions in urban cities may have different reception ability, e.g., receivers on a square, are more likely to have small path loss exponent (PLE) value compared with receivers located in between skyscrapers. Fig 2 shows a simple example of block-based path loss model, realistic model based on the real city structure can be considered as future work.

Remark 1 *It should be noticed that, if given a specific city structure, the block-based model can also be extended to irregular shapes extracted from the empirical environments. Proposition 1 provides a solution of defining the PLE level depending on the obstacles in the environment.*

3 Construction of ANN

An ANN, aiming at solving regression problems are constructed. Inputs of the ANN are selected from possible influential factors in determining EMF exposure, which is, distance between receiver and BS, time of the measurement, azimuth of antennas and city structure in terms of blocked-based PLE.

To minimize the cost function, back propagation is performed by applying gradient descend method. And to better evaluate the performance of the ANN, two metrics are used in the present paper, mean square error (MSE) and R^2 [5] ,where MSE approach is used to minimize residual sum of squares (RSS). R^2 indicates how close two sets of data are. When $R^2 \to 1$, a large proportion of the variability in the response is explained by the ANN.

4 Results

We presented results of EMF exposure reconstructed by using ANN in this section. Additive noise is added with SNR = 15dB and time variation in Section 2 is considered. To feed the ANN, inputs are selected according to the feasibility in practical measurements, including 1) distances to 10 nearest BSs; 2) azimuth of antenna; 3) time of measurement; 4) location of receiver.

In total we have 3516 data sets generated from simulations in Matlab. A minimum separation distance is considered when splitting total datasets, in order to make sure diversity of training data. Early stopping method is used to avoid over-fitting. Standardization approaches are used to preprocess inputs of ANN. In the training data, 33% them is used as validation. With different percentage of selecting training data, we are able to reconstruct the EMF exposure with R^2 up to 0.767.

In Table 1, different portion of training and testing data are explored. In total, we have 3516 datasets, with division them into half training and half testing, we are able to achieve $\mathrm{R}^2 = 0.767$. With the decreasing number of training data, the performance if prediction is decreasing as expected. However, even if when percentage of training is lower than 10%, the R^2 is is still around 50%, which can be explained by strong correlation between inputs and output.

Table 1. Performance of ANN under different percentage of training and testing data.

Training	Testing	$\mathbf{R}^2$
50%	50%	0.767
37%	63%	0.753
28%	72%	0.720
14%	86%	0.705
9%	91%	0.523
3%	97%	0.478

Fig 3 shows the scattering plot of target obtained from simulations and predictions generated by ANN. The closer the scattering points get to the black diagonal line, the more accurate predictions are. Both training and testing results, denoted by blue and red dots respectively, show good ability

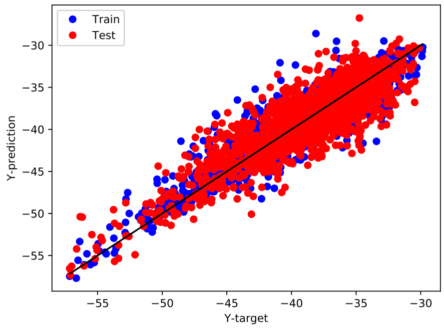

Figure 3. *Scattering plot of training and testing data*

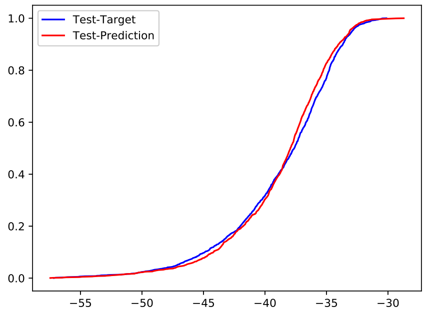

Figure 4. *CDFs of targets and predictions from ANN.*

in reproducing the EMF exposure. Fig 4 illustrates cumulative distribution function (CDF) for targets and predictions of testing data, which shows a good overlap between predictions and targets as well.

5 Conclusion

In this work, we reconstruct EMF exposure from 4G networks given measurements recorded by sensors. We are able to take into account key factors as, distance to the BS, azimuth of antennas, time of measurement, and most importantly, the blockages in the urban environment. A new block-based model taking consideration of terrain and environment is proposed. This new model can provide a solution to reproduce the LoS and NLoS rays caused by complicated building structure. We are able to achieve that under a realistic scenario mentioned above, predictions from ANN has R^2 up to 0.767.

References

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