EME-GAN: A Conditional Generative Adversarial Network based Indoor EMF Exposure Map Reconstruction

Mohammed MALLIK[1] Benjamin ALLAERT[2] Angesom TESFAY[2] Davy P. GAILLOT[1] Joe WIART[3] Laurent CLAVIER[1,2]

[1]Univ. Lille, CNRS, Centrale Lille, Univ. Polytechnique Hauts-de-France, UMR 8520 -IEMN -Institut d'Electronique de Microélectronique et de Nanotechnologie, F-59000 Lille, France,

[2]IMT Nord Europe, Institut Mines-Télécom, Univ. Lille, Centre for Digital Systems, F-59000 Lille, France

[3]Chaire C2M, LTCI, Télécom Paris, Institut Polytechnique de Paris, Palaiseau, France

Correspondence: Mohammed Mallik (email: firstname.name.etu@univ-lille.fr)

Résumé – Les nouvelles technologies de communication sans fil se développent de façon exponentielle. Parallèlement des craintes sont apparues concernant de possibles effets délétères des ondes électromagnétiques de type radiofréquence sur la santé. Cet article propose une méthode basée sur un réseau génératif conditionnel pour la cartographie de l'exposition aux champs électromagnétiques en environnement intérieur, appelée EME-GAN. En s'appuyant sur la cartographie du bâtiment et de quelques points de mesure d'exposition, le modèle proposé est capable d'inférer une carte réaliste des caractéristiques de la propagation des signaux sans fil. Les résultats démontrent que le modèle estime fidèlement les phénomènes de propagation.

Abstract – New wireless communication technologies are developing exponentially. Meanwhile, concerns have arisen about the possible negative health effects of radiofrequency electromagnetic waves. This paper proposes a method based on a conditional generative adversarial network for the mapping of exposure to electromagnetic fields in an indoor environment, called EME-GAN. Based on the building map the proposed model is able to infer a realistic map of wireless signal propagation characteristics based on a few measurement points. The results show that the model accurately estimates the propagation phenomena.

1 Introduction

The perceived risk of exposure to radiofrequency electromagnetic fields (RF-EMFs) [13] is currently a hot topic due to rapid advances in wireless communications. The assessment of this risk is essentially based on the ability to clearly identify how electromagnetic fields propagate in the indoor environment. Despite advances in this field, the wide variety of parameters, e.g., materials, sensor arrangement, or room size, make this task relatively complex and often requires a large number of measurements, both time-consuming and expensive. Auto-encoders have demonstrated their ability to infer complex information based on sparse representations of the input data [8], and seem perfectly suited to address this issue.

Related works. Often based on standard kriging interpolation methods [9], neural network-based approaches tend to provide very good performances. In [7], authors propose to infer electromagnetic field exposure from Wi-Fi access points in a realistic indoor environment focused on frequencies from 2.412 GHz to 2.472 GHz, based on the U-net architecture [12]. Although the approach gives promising results, the inference of the electromagnetic field contains some anomalies, as the model does not allow to take into account the constraints related to the building infrastructure. In [4], authors estimated the power spectrum map for urban cognitive radio networks by using a Generative Adversarial Network (GAN) [3]. The proposed approach requires that the users are evenly distributed and the frequencies used are between 25 MHz and 75 MHz. A deep learning regression task is used to generate the power spectrum maps, which are then mapped to a color scale. These power spectrum maps are used to drive a GAN model. The inverse polynomial law model is the only one that the authors were able to use to represent the propagation processes in the estimated power spectrum maps (PSM). Although generative models have been shown to be effective in addressing this issue, current approaches do not take into account the strong constraints related to the infrastructure, e.g., structure, size, and materials. In order to infer a realistic electromagnetic field, the consideration of this information is essential. Recent works based on conditioned GAN models [8], where inference is conditioned by rules, e.g., physical laws or structural constraints, tend to better address this issue. However, no solution based on this architecture has been proposed so far for the analysis of indoor electromagnetic field inference.

Goals and outline In this paper, we propose a conditional Generative Adversarial Network (cGAN) architecture called EME-GAN. It consists in training a generative model by presenting the problem as a supervised learning problem with two sub-models. The two models are trained together in a zero-sum game, adversarial, until the discriminator model is fooled about half the time, meaning the generator model is generating plausible examples. The proposed model is designed to learn and reconstruct the features of indoor wireless propagation, such as reflection, diffraction, shadowing, and the impact of building walls and materials. The paper is organized as follows. In Section 2, we describe the implementation details and the dataset. Section 3 presents the proposed EME-GAN model for RF-EMF indoor exposure power map estimation. Experimental findings are presented and discussed in Section 4. The conclusion is given in Section 5.

2 Implementation Details and Dataset

Dataset. A modified version of the WINNER-II environment, a widely used propagation scenario [10] is used to generate the training set. The floor space is 2100 m^2, the room dimensions are $10m \times 10m \times 3m$, and the corridor's measurements are $70m \times 10m \times 3m$. This illustrates a typical multi-room office setup. Both the north and south sides of the workplace space have windows. There are wooden doors in each room, and the walls are made of $10cm$ thick plaster. Reinforced concrete was used to create the ceiling and floor. The configuration of the indoor building environment is used to constrain the generative model to build consistent outputs. The complete exposure reference maps are generated using 'Pylayers', an open-source program [1] for simulating radio-channel wave propagation. Figure 1-A, gives one example of a reference exposure map with four Wi-Fi access points locations.

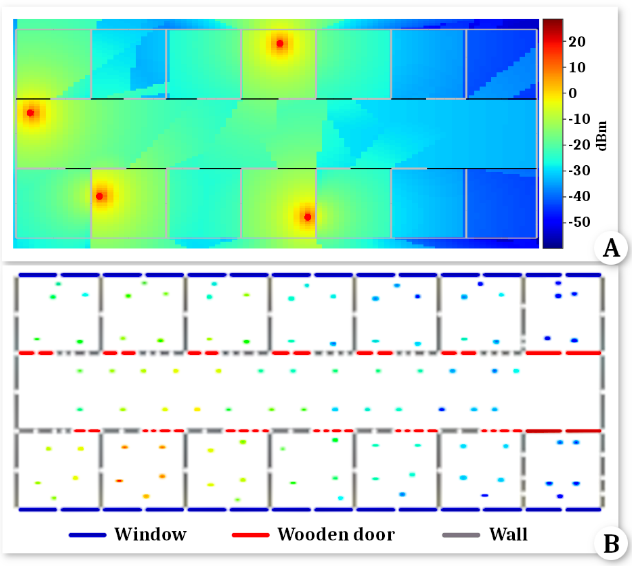

Figure 1 – RF-EMF exposure reference map (ieee 80211b, fc=2.412 GHz polar: p). The red dots represent the Wi-Fi access points. The color gradient corresponds to the power of the electromagnetic field.

Data preparation. The input data consists in a small number of information in the different rooms of the building, corresponding to different measurements, more or less accurate, as illustrated in Figure 1-B. For this, 96 pixels were chosen from the reference map: 5 measures in each room, and 26 measures in the hallway. For the test sets, we take into account 30, 60, and 96 pixels from the reference map pictures. Notably, we only cover less than 1% of the reference image area in the most optimistic case, i.e., when 96 measurements are taken into account. The multi-wall and multi-frequency home environment path loss model [6] is taken into account when creating the EMF exposure maps.

To generate the reference maps, the same room is selected while different access point locations are used at different frequencies, transmit power, polarization - orthogonal and parallel, and antenna orientations. A total of 2249 reference maps are generated using these configurations, where 2087 are used for training and validation and 162 are used as unseen data for testing.

3 Exposure Map Estimation GAN

Given a sparse exposure map corresponding to few measurement points, G_F estimates the mapping of exposure to electromagnetic fields in the indoor environment induced by the Wi-Fi access points $\tilde{y}^* = G_F(y)$ to match the ground truth exposure map $y^* \in Y^*$.

In the following, we present our proposed EME-GAN architecture, which is mainly based on a U-Net generator G_F and a PatchGAN discriminator D_P. An overview of the proposed architecture is given in Figure 2.

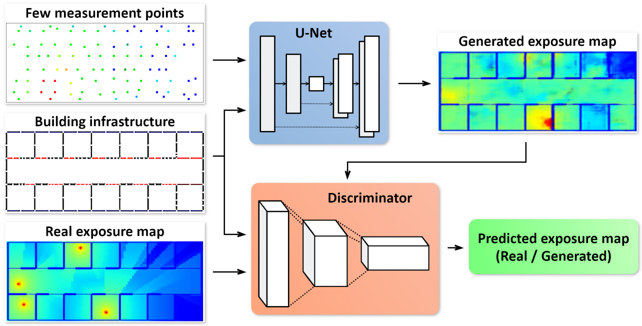

Figure 2 – Overview of the proposed EME-GAN architecture.

Exposure Map Generator. The underlying architecture comprises an encoder network and a decoder network with residual blocks as a bottleneck. The input and the output of the network are set to be $128 \times 128 \times 3$.

The encoder consists of 4 downsampling, each with 2D convolution, an instance normalization, and a ReLU. For the first layer, reflection padding is added to avoid checkerboard artifacts. Two residual blocks are added to continue the encoding of the electromagnetic field measurements. The residual blocks include a 2D convolution, an instance normalization, and a ReLU.

The decoder processes the encoded power of the electromagnetic field with 5 residual blocks and reconstructs the exposure map with 4 upsampling, each with a 2D convolution, a layer normalization with affine transformation parameters, and a ReLU.

PatchGAN Discriminator. Inspired by the Pix2Pix GAN discriminator [5], we propose our discriminator based on PatchGAN. It solely discriminates on the basis of patch-level information, which is more computationally efficient as it requires fewer parameters. In addition, discriminators that rely on the whole image can suffer from overconfidence, i.e., if the discriminator relies mainly on a small set of features to distinguish real from fake images, the generator can produce these features accurately to fool the discriminator.

Although control techniques such as dropout or label smoothing can be introduced to mitigate this problem, the PatchGAN discriminator is more suitable, as it does not suffer from this problem due to patch-level discriminations. Each block of the proposed architecture consists of a 2D convolution layer with a kernel size of 4 and a stride size of 2, an instance normalization, and a Leaky ReLU which makes the gradients less sparse.

3.1 Loss Functions

For a standard conditional GAN, the objective function which refers to the conditional adversarial loss function is formulated as [11]:

$$\mathcal{L}_{cGAN}(G, D) = \mathbb{E}_{X,Y}[\log D(Y)] + \mathbb{E}_{X,Y}[\log(1 - D(X, G(X, Z)))] \tag{1}$$

where the model tries to learn the mapping $G : \{X, Z\} \mapsto Y$, X is the source domain, Y is the target domain and Z is the noise sample. The generator tries to minimize this loss while the discriminator tries to maximize it.

Generator Loss. The L1 loss which is the mean absolute error (MAE) between the generated image and the target image is used in this architecture. Although this loss function can cause the generated image to become structurally similar to the target image, it has been shown to be effective in addressing this problem. The loss function of the Generator network results in:

$$G^* = arg\ min_G\ max_D\ L_{cGAN}(G, D) + \lambda \mathcal{L}_{L1}(G) \tag{2}$$

4 Evaluation

For the evaluations, we train our model on samples corresponding to 96 measurement points. The performance of the model is investigated on different measurement scenarios, ranging from 30, 60 to 90 measurement points.

In this section, we conduct a quantitative and qualitative experiment on the evaluation dataset. We compare the results of our EME-GAN method with those obtained by our previous EME-NET method adapted to reconstruct indoor electromagnetic fields.

4.1 Quantitative comparison

Both average structural similarity index measure (SSIM) and Peak signal-to-noise ratio (PSNR) increase along with the number of measurement locations are shown in Figure 3. The use of global raw pixel intensities is the reason for the small decline in the average SSIM at 96 measurements. The same trend indicates that the reconstruction process is coherent with respect to similarity and image quality.

The probability density function (PDF) of the ratio of the reconstructed maps to the ground truth for the proposed EME-GAN model and EME-Net, is shown in Figure 4. A Gaussian random variable can be used to closely approach the error ratio (in dB) distribution. The first thing we note is that the mean is very low, indicating that there is not much bias in the prediction stages. The second crucial observation is that, as the number of sensors increases, the variance decreases.

Figure 5 shows the Cumulative Distribution Function (CDF) of the error ratio R, which is the comparison of the reconstructed map to the reference map, for the proposed EME-GAN and another model with varying numbers of sensors. Moreover, Figure 5 demonstrates that, despite the upbeat visual evaluation, the performance of the suggested EME-GAN declines with a reduction in the number of sensors.

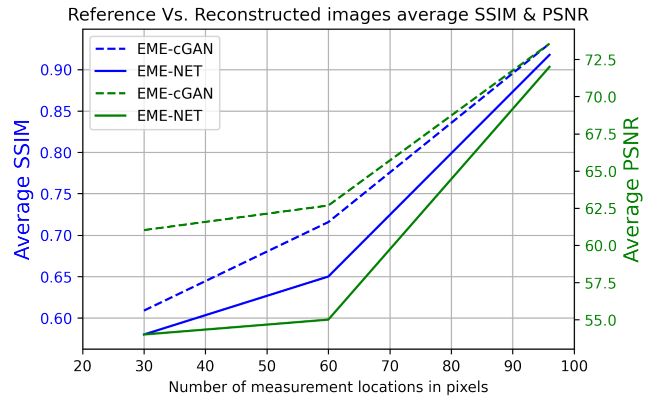

Figure 3 – PSNR and SSIM comparison with a different number of measurements.

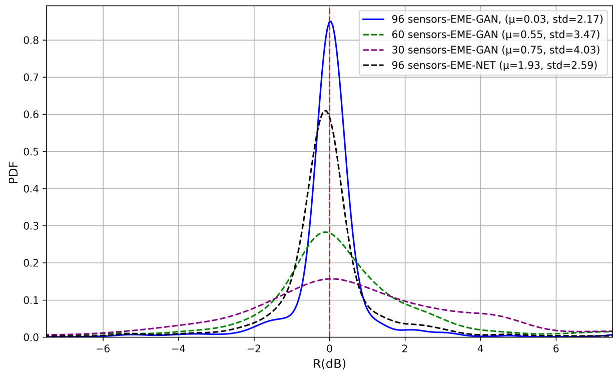

Figure 4 – Probability Density Function (PDF).

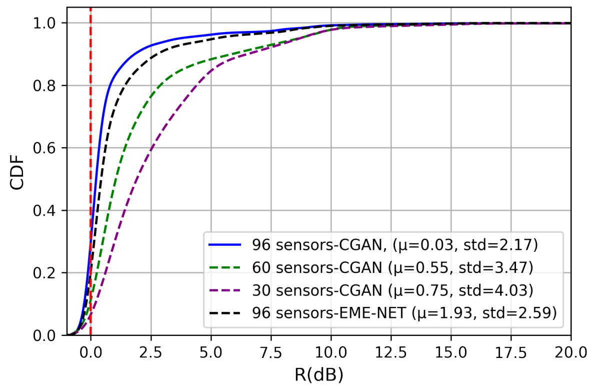

Figure 5 – Cumulative distribution function (CDF).

4.2 Qualitative comparison

The EME-GAN model's reconstructed maps are illustrated in Figure 6 with 5 access points in training data. With only 60 measurement points, the EME-NET reconstruction falls short and fails to represent the reference map. In addition, with an increased number of measurement points (96), our model outperforms EME-NET with better reconstruction quality and a low error ratio R near zero. Even with 8 access points as unseen data, our model performs well and surpasses EME-NET in reconstruction compared to the reference map.

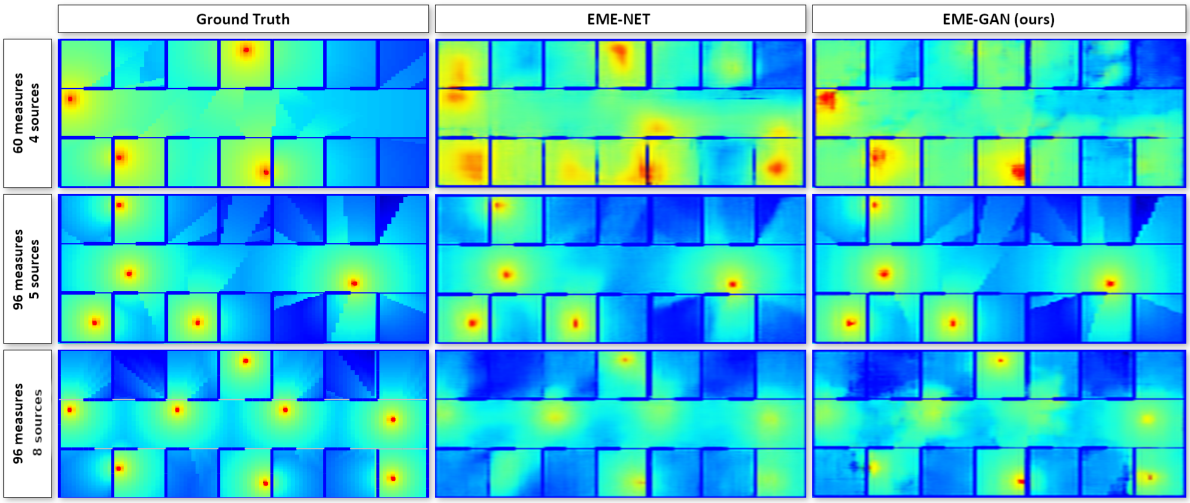

Figure 6 – Comparison of inferred exposure maps from different measurement points configurations.

5 Conclusion and future work

This study proposed a conditional generative model-based approach for estimating RF-EMF exposure maps for indoor wireless networks, known as EME-GAN. The suggested EME-GAN was developed to accurately predict the RF-EMF exposure maps using a conditional GAN architecture. The results prove that the proposed model is able to correctly predict exposure maps with few measurements taken at random locations in the building, i.e.with less than 1% of the reference map area. Instead of relying on weak or biased signal propagation assumptions, the model learns the propagation characteristics of the complex indoor radio environment by taking into account the building characteristics. In the future, we plan to improve the model architecture by integrating more suitable loss functions to enhance the quality of the electromagnetic field reconstruction.

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