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Magnetic Field Prediction Using Generative Adversarial Networks

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Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

Citation (APA):
Pollok, S., Olden-Jørgensen, N., Jørgensen, P. S., & Bjørk, R. (2022). *Magnetic Field Prediction Using Generative Adversarial Networks*. 542-542. Abstract from 15th Joint MMM-Intermag Conference, New Orleans, United States.

the pillars were carried out under the same conditions used in the essays to better understand the magnetization dynamics and magnetostrictive effect. It is shown how the morphology and the application of the magnetic field to the nanostructured surface affects bacteria killing, becoming a proof-of-concept for nanostructured magnetically activated materials for the development of antimicrobial surfaces. The authors acknowledge the IEEE Magnetics Society for the Eductaional Seed Funding.

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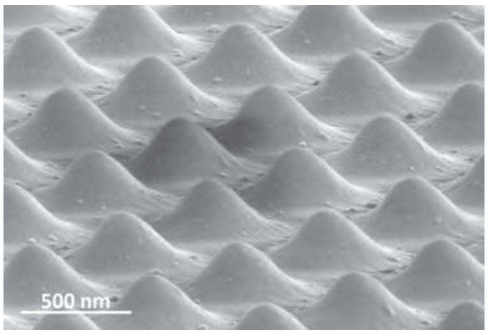

Fig 1. SEM image of the Terfenol-D pillars deposited over a Si substrate.

IOI-10. Green Synthesis and Characterization of Magnetic Fe_3O_4, $CoFe_2O_4$ and $NiFe_2O_4$ from Aloe Vera Extract and its Biomedical Potential. *G.C. Hermosa*[1] and A. Sun[1] *1. Yuan Ze University, Taoyuan, Taiwan*

The magnetic nanoferrites (Fe, Co, Ni) were prepared by an eco-friendly hydrothermal method using an Aloe Vera plant extract solution as both a reducing and stabilizing agent. Magnetic nanoferrites were characterized using XRD, VSM, SEM, TEM and XPS. Cytotoxicity were obtained using the MTT assay. X-ray diffraction analysis also demonstrated that the size range of the nanoferrites exhibited average diameters of 8-29 nm and also exhibiting high crystallinity. Results showed that all the metallic nanoparticles are magnetic with values Fe = 52 emu/g, Co = 33 emu/g and Ni = 7.1 emu/g. The magnetic nanoferrites exhibited high cell viability rate at high concentrations signifying their non-toxic property. From SEM, spherical structure was noticeable and the particle size is also in accordance with XRD. The chemical states for each nanoparticle also confirmed the successful synthesis of each nanoferrite. The magnetic nanoferrites produced in this study by green synthesis methodology from leaf extract of Aloe Vera needs to be further evaluated and could find greater biomedical application.

[1] N. Guijarro, P. Bornoz, M. Prévot, X. Yu, X. Zhu, M. Johnson, X. Jeanbourquin, F. Le Formal and K. Sivula, Sustainable Energy & Fuels 2, (2018). [2] Sun, H. Zeng, D. Robinson, S. Raoux, P. Rice, S. Wang and G. Li, Journal of The American Chemical Society 126, (2004). [3] S. Hazra and N. Ghosh, Journal of Nanoscience and Nanotechnology 14, (2014). [4] M. Irfan Hussain, M. Xia, Xiao-NaRen, K. Akhtar, A. Nawaz, S. Sharma and Y. Javed, Magnetic Nanoheterostructures (2020). [5] S. Bhagyaraj, *Synthesis of Inorganic Nanomaterials* (2018).

IOI-11. Magnetic Field Prediction Using Generative Adversarial Networks. *S. Pollok*[1*], N. Olden-Jørgensen[1], P.S. Jørgensen[1] and R. Bjørk[1] *1. Department of Energy Conversion and Storage, Technical University of Denmark, 2800 Kgs. Lyngby, Denmark*

We present a novel approach to predict magnetic field values at a random point in space from a few point measurements by using deep learning (DL). For this data-driven approach, we produce a large dataset of 20,000 samples with MagTense [1]. Each sample is a magnetic field of resolution 256 × 256 in the center of a 2-D grid, which is surrounded by multiple randomly placed hard magnets with varying magnetization. The DL architecture, inspired by Ref. [2], is depicted in Fig. 1. For the underlying Wasserstein generative adversarial network [3], we train two neural networks: a generator, which predicts the missing field values of a magnetic field, and a critic, which calculates the Wasserstein-1 distance [4] between real and generated field distributions. In addition to minimizing the Wasserstein-1 distance, the network parameters of the generator are updated to lower the L1 reconstruction loss between real and predicted field values. This setup can either be trained on inpainting, where the generator predicts missing field values in a specific region, or in an inverted way, a so-called outpainting task, where small patches across the measurement area are available and the field values around are predicted, as shown in Fig. 2. Given a sample, which was not included in the dataset used for training, the generator has learned to accurately predict the missing field values, which correspond excellently to the real magnetic field. The median reconstruction error of 1,000 test samples on inpainting is 5.09%, while it is 9.58% on outpainting. With this approach, we pave the way to replacing parts of expensive field measurements or calculations by filling the required measurement area with values generated by a trained neural network. Moreover, it can serve as a preprocessing step for the inverse design of magnetic fields [5]. We are currently working on extending the DL architecture for a magnetic field measured in a 3-D volume.

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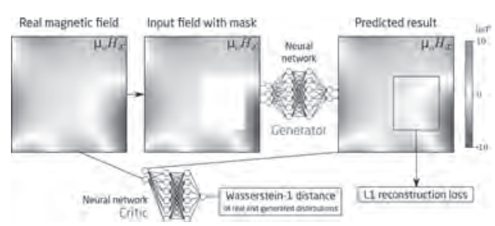

Fig. 1. Novel DL approach for magnetic field prediction. A generator is trained to predict the missing field values, which are subsequently evaluated by a trained critic and the L1 reconstruction loss.

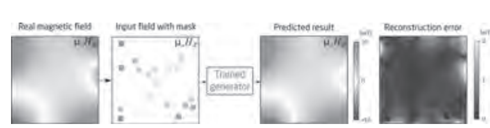

Fig. 2. Qualitative analysis of the trained generator on outpainting with an unseen test sample.