Recognizing the face of wave functions

Luis S. Froufe-Pérez
Augustin Muster, Geoffroy J. Aubry

Department of Physics, University of Fribourg, Chemin du Musée 3, 1700 Fribourg, Switzerland.

luis.froufe@unifr.ch

Electromagnetic wave transport through disorder and correlated media shows a rich phenomenology. Depending on the degree of correlation and frequency, different light transport regimes emerge, while keeping other relevant parameters constant such as density and optical properties of scatters.

In this context, two dimensional stealthy hyperuniform structures (SHU) [1] have been recognized to present at least five different transport regimes, namely transparency [2], diffusion, Anderson localization, pseudo-tunneling [3] and tunneling through complete stop bands [4].

Determining the transport regime associated to an individual wave function has been traditionally addressed by computing the inverse participation ratio (IPR)[5] associated to the wave function. IPR estimates the number of scattering units involved in the build up of a particular wave function. Small values of IPR are associated to delocalized modes, while a large IPR corresponds to localized modes. Nevertheless, IPR and its generalized versions can not account for the variety of transport regimes found in SHU media.

Motivated by the successful application of machine learning techniques in this field [6], in this work we take a machine learning approach based on artificial neural networks to determine the transport regime associated to a particular wave function. A convolutional neural network (CNN), called EfficientNet [7], is trained with field maps of more than 200'000 wave functions, labeled with its corresponding transport regime.
In our implementation we take advantage of most of the architecture of the CNN, designed to perform high accuracy image recognition, and adapt it by knowledge-transfer to perform wave function recogntion.

When new field maps are shown to the neural network, we obtain a high accuracy (>92%) on the predictions on the transport regimes.

It is worth noting that no information about the frequency or structure of the underling scattering system is presented to the artificial neural network.

In this work we discuss the ability of the neural network to successfully generalize to new data sets without re-training in cases where IPR is not a good indicator.

References

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