	doc_1	doc_2	decision	id
cases			DUPLICATES	44

doc_1

authors	• Conlain Kelly • Surya R. Kalidindi
title	Recurrent Localization Networks applied to the Lippmann-Schwinger Equation
publication_date	2021-01-29 20:54:17+00:00
source	SupportedSources.ARXIV
journal	Computational Materials Science Volume 192, May 2021, 110356
volume	
doi	10.1016/j.commatsci.2021.110356
urls	• http://arxiv.org/pdf/2102.00063v2 • http://dx.doi.org/10.1016/j.commatsci.2021.110356 • http://arxiv.org/abs/2102.00063v2 • http://arxiv.org/pdf/2102.00063v2
id	id37583091022075957
abstract	The bulk of computational approaches for modeling physical systems in materials science derive from either analytical (i.e. physics based) or data-driven (i.e. machine-learning based) origins. In order to combine the strengths of these two approaches, we advance a novel machine learning approach for solving equations of the generalized Lippmann-Schwinger (L-S) type. In this paradigm, a given problem is converted into an equivalent L-S equation and solved as an optimization problem, where the optimization procedure is calibrated to the problem at hand. As part of a learning-based loop unrolling, we use a recurrent convolutional neural network to iteratively solve the governing equations for a field of interest. This architecture leverages the generalizability and computational efficiency of machine learning approaches, but also permits a physics-based interpretation. We demonstrate our learning approach on the two-phase elastic localization problem, where it achieves excellent accuracy on the predictions of the local (i.e., voxel-level) elastic strains. Since numerous governing equations can be converted into an equivalent L-S form, the proposed architecture has potential applications across a range of multiscale materials phenomena.
versions	

doc_2

authors	• Conlain Kelly • Surya R. Kalidindi
title	Recurrent Localization Networks applied to the Lippmann-Schwinger Equation
publication_date	2021-01-29 00:00:00
source	SupportedSources.INTERNET_ARCHIVE
journal	
volume	
doi	
urls	• https://web.archive.org/web/20210203192707/https://arxiv.org/pdf/2102.00063v1.pdf
id	id8760893955965276234
abstract	The bulk of computational approaches for modeling physical systems in materials science derive from either analytical (i.e. physics based) or data-driven (i.e. machine-learning based) origins. In order to combine the strengths of these two approaches, we advance a novel machine learning approach for solving equations of the generalized Lippmann-Schwinger (L-S) type. In this paradigm, a given problem is converted into an equivalent L-S equation and solved as an optimization problem, where the optimization procedure is calibrated to the problem at hand. As part of a learning-based loop unrolling, we use a recurrent convolutional neural network to iteratively solve the governing equations for a field of interest. This architecture leverages the generalizability and computational efficiency of machine learning approaches, but also permits a physics-based interpretation. We demonstrate our learning approach on the two-phase elastic localization problem, where it achieves excellent accuracy on the predictions of the local (i.e., voxel-level) elastic strains. Since numerous governing equations can be converted into an equivalent L-S form, the proposed architecture has potential applications across a range of multiscale materials phenomena.
versions	