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abstract	This paper introduces a neural network approach for solving two-dimensional traveltime tomography (TT) problems based on the eikonal equation. The mathematical problem of TT is to recover the slowness field of a medium based on the boundary measurement of the traveltimes of waves going through the medium. This inverse map is high-dimensional and nonlinear. For the circular tomography geometry, a perturbative analysis shows that the forward map can be approximated by a vectorized convolution operator in the angular direction. Motivated by this and filtered back-projection, we propose an effective neural network architecture for the inverse map using the recently proposed BCR-Net, with weights learned from training datasets. Numerical results demonstrate the efficiency of the proposed neural networks.	This paper presents a neural network approach for solving two-dimensional optical tomography (OT) problems based on the radiative transfer equation. The mathematical problem of OT is to recover the optical properties of an object based on the albedo operator that is accessible from boundary measurements. Both the forward map from the optical properties to the albedo operator and the inverse map are high-dimensional and nonlinear. For the circular tomography geometry, a perturbative analysis shows that the forward map can be approximated by a vectorized convolution operator in the angular direction. Motivated by this, we propose effective neural network architectures for the forward and inverse maps based on convolution layers, with weights learned from training datasets. Numerical results demonstrate the efficiency of the proposed neural networks.		
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