Wave-dynamics simulation using deep neural networks

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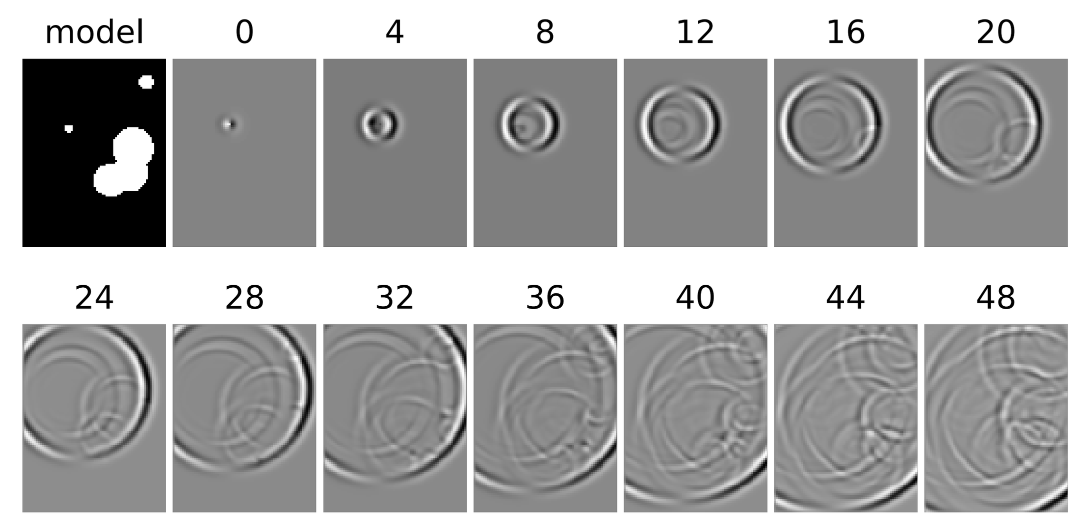
1. Introduction

When we see an apple falling from a tree, or a ball throwing at us, we can predict where the apple or the ball would go in just seconds. Obviously, we do not form physics equations and solve it in our mind to get the answers. Instead, our prediction is based on our observation and experience.

But can machine learn the basic physical instinct just like us? Can neural networks make long-term predictions based on observations without explicitly solving the underlying physical laws? In this project we are try to apply deep neural networks on wave-dynamics simulation to test if the neural network can predict the propagation process of waves. The neural network is trained by 'watching' tons of seismic waves propagating through different media. No physical equations or numerical approximation methods are fed into the neural network. The training data and test data are generating using a numerical simulation code for seismic waves. The results show that the neural network is able to predict the following frames of wave propagation given only the first several frames.

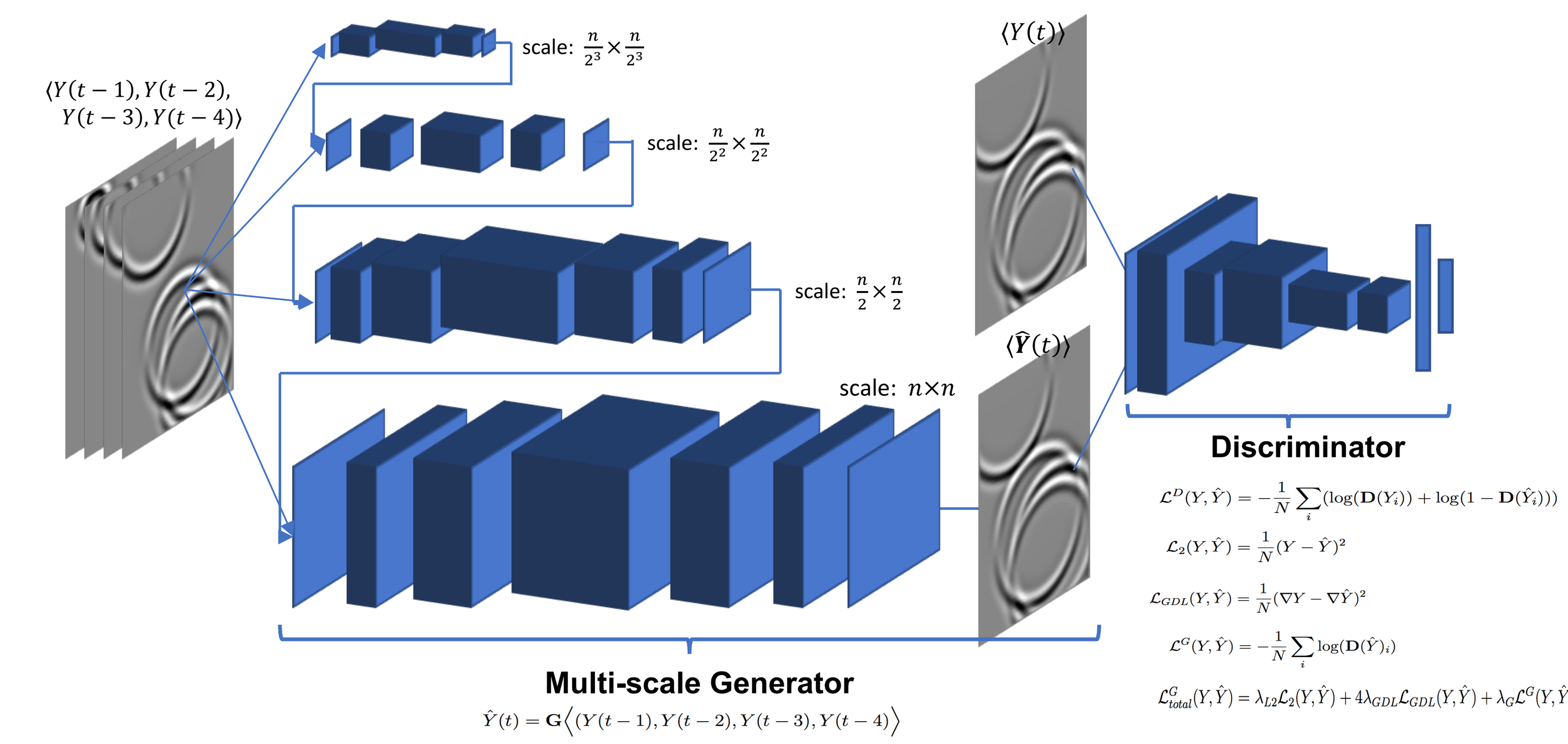
2. Data

A 2-D seismic wave numerical simulator [1] is used to generate wavefields as training and testing data. Parameters we change during simulations are: source number, source location, P wave velocity, S wave velocity and material density. We have generated two datasets: one with homogeneous velocity and density; the other one has velocity and density anomalies embed in the material. So the simulations data includes different seismic wave phenomenon: reflection, refraction, P-to-S or S-to-P conversion, heterogeneous propagation velocity.

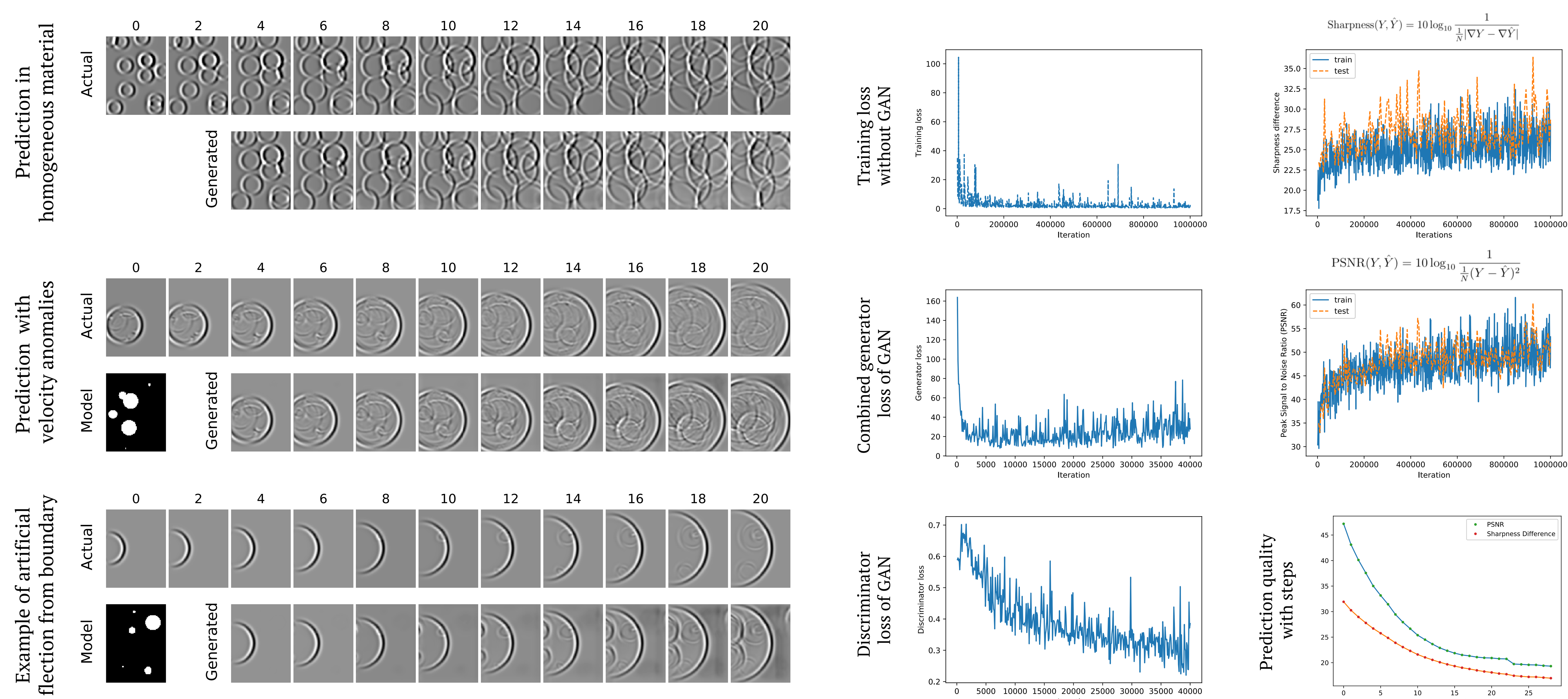


3. Method

We use the method in video prediction [2] to train a ConvNet to learn an end-to-end mapping that predicts the wavefields at continuous time-steps. The multi-scale generator consists of four mini ConvNets of different input and output sizes in order to better reserve the sharpness of the generated wavefields. Generative adversarial network is also tested to further improve the quality of the predictions.



4. Result



5. Discussion

The neural network successfully learns from physical simulation and gives good predictions of wavefields of following time-steps in both homogeneous and complex media. However, we also observe some problems that limits the accuracy and robustness of results:

1. Prediction quality decrease as time step increases. This is a problem of recursive prediction, the errors will accumulate through time. How to ensure long-time steps stability is still challenging.
2. Abnormal reflections from boundaries. In some examples with complex media, we find some reflections on the boundary which don't exist in the actual simulation data. One possible cause could be the model misunderstands the boundary as obstacles and gives reflections.
3. GAN achieves little improvement. The improvement in GAN is not as obvious as we thought. Different ratios of learning rates between the generator and the discriminator and different ratios between three losses are tested. Further fine-tuning of the hyper-parameters is needed.

6. Reference

[1] Komatitsch, D., & Martin, R. (2007). An unsplit convolutional perfectly matched layer improved at grazing incidence for the seismic wave equation. *Geophysics*, *72*(5), SM155-SM167.
[2] Mathieu, M., Couprie, C., & LeCun, Y. (2015). Deep multi-scale video prediction beyond mean square error. *Iclr*, (2015), 1–14.
[3] Tompson, J., Schlachter, K., Sprechmann, P., & Perlin, K. (2016). Accelerating Eulerian Fluid Simulation With Convolutional Networks.