Deep learning InSAR: atmospheric noise removal and small deformation signal extraction from InSAR time series using a convolutional autoencoder

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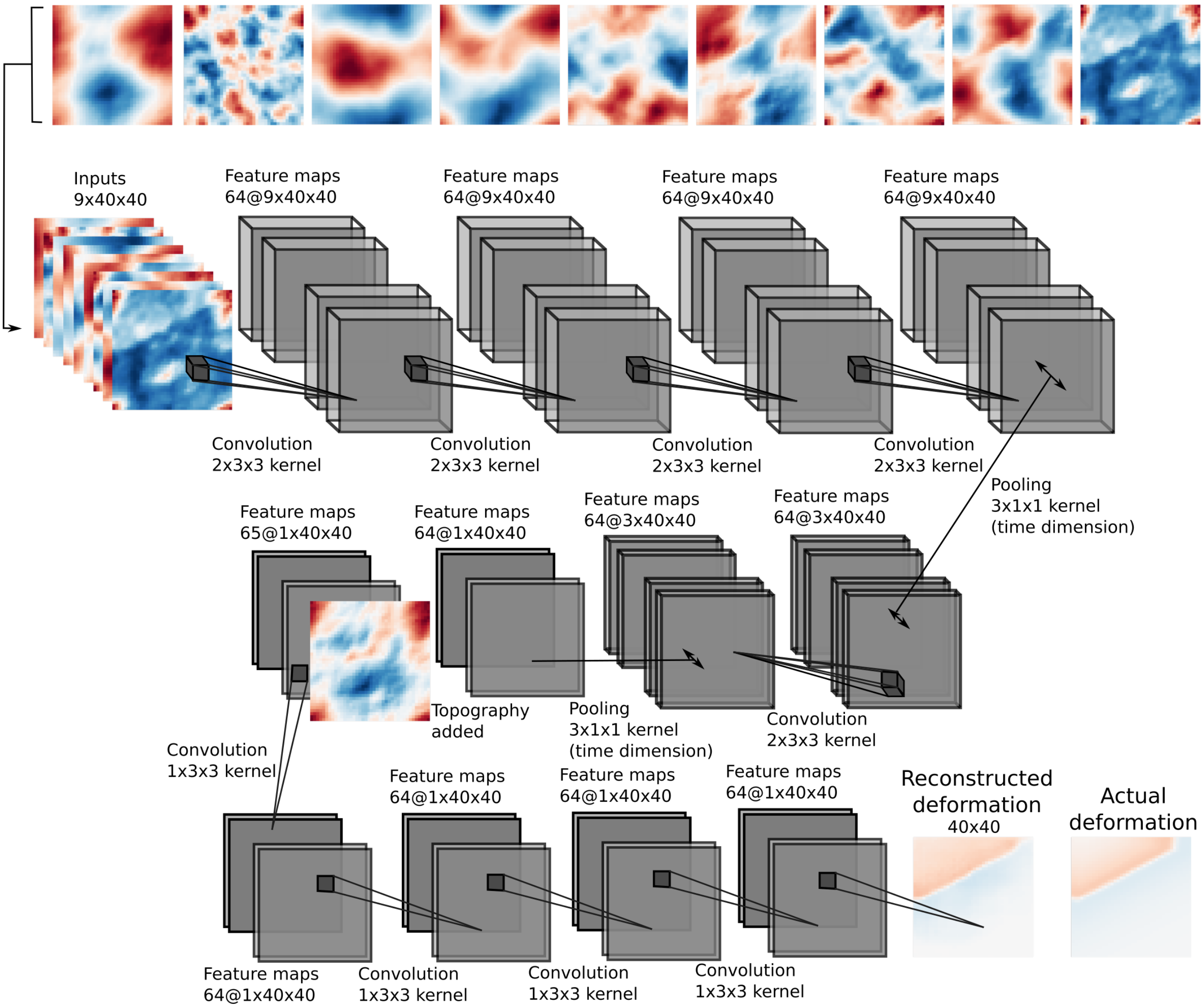
Spatial and temporal variations of pressure, temperature, and water vapor content in the atmosphere introduce significant errors in interferometric synthetic aperture radar (InSAR) observations of ground deformation. Large amplitude and fast deformations produced during earthquakes are routinely measured using InSAR. However, Interseismic and postseismic deformation -- both smaller and slower -- remains extremely challenging to measure due to atmospheric propagation delays, even after correction for known atmospheric conditions, therefore requiring expert interpretation and *a priori* knowledge of fault systems. To solve this problem, we introduce a deep autoencoder architecture that is tailored to remove atmospheric delays due to turbulences and the layering of the atmoshpere, as well as to identify and extract ground deformation signals of interest. Taking noisy InSAR time series as input and cumulated ground deformation of interest as output, the deep autoencoder we built is purely convolutional, shrinks the time dimension during the encoding, and uses the ground elevation during the decoding. In order to circumvent the lack of training data and the absence of deformation ground truth, we train our model on simulated data in which small synthetic fault deformation signals are heavily corrupted by statistically realistic atmospheric signals. After training on a few million examples of synthetic InSAR time series, application on real InSAR time series reveals very clean and sharp deformation signals on faults known to be deforming, with no *a priori* knowledge of fault systems. The proposed deep autoencoder approach enables the automation of denoising and signal extraction from InSAR time series, making possible the study of small deformations at a global scale.

Keywords: Machine learning, InSAR


Inputs
9x40x40
Feature maps
64@9x40x40
Feature maps
64@9x40x40
Feature maps
64@9x40x40
Feature maps
64@9x40x40
Convolution
2x3x3 kernel
Convolution
2x3x3 kernel
Convolution
2x3x3 kernel
Convolution
2x3x3 kernel
Pooling
3x1x1 kernel
(time dimension)
Feature maps
65@1x40x40
Feature maps
64@1x40x40
Feature maps
64@3x40x40
Feature maps
64@3x40x40
Topography
added
Pooling
3x1x1 kernel
(time dimension)
Convolution
2x3x3 kernel
Convolution
1x3x3 kernel
Feature maps
64@1x40x40
Feature maps
64@1x40x40
Feature maps
64@1x40x40
Reconstructed
deformation
40x40
Actual
deformation
Feature maps
64@1x40x40
Convolution
1x3x3 kernel
Convolution
1x3x3 kernel
Convolution
1x3x3 kernel

