Unsupervised feature learning and automatic detection of transient phenomena in InSAR time-series

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Detecting and measuring transient episodes of crustal deformation is important for a wide range of solid earth and natural hazard applications, e.g. for improving understanding of seismic and volcanological hazards and for monitoring anthropogenic deformation. InSAR is one of the most suitable techniques for this purpose, due to the frequent, regular and global coverage of current-generation satellite missions. However, both the size of the global InSAR dataset, and the large magnitude of atmospheric and other nuisance signals relative to deformation signals of interest, makes this task difficult and precludes systematic manual analysis.

In order to address this issue, here we have developed a new, state-of-the-art deep-learning based approach for the automatic identification of transient deformation events in noisy time-series of unwrapped InSAR images, without requiring supervision or labelling of known example events. To achieve this, we have adopted an anomaly detection framework where anomalies correspond to any transient phenomena that deviates from the ‘normal’ spatio-temporal pattern of phase-change (predominantly due to changes in atmospheric conditions). Our novel workflow learns such patterns in the InSAR dataset, leveraging the unique three-dimensional structure of the interferogram stack and its relationship to the unknown 2D fields of nuisance non-tectonic signals that correspond to individual SAR acquisition dates (epochs). This approach offers major benefits over previously published work using machine-learning to detect signals in InSAR data; those attempts have either largely focused on learning spatial or temporal patterns alone and/or have required an extensive ‘labelled’ dataset of known signals of interest, precluding detection of any signals with different or unexpected spatio-temporal characteristics.

In detail, our framework includes fully convolutional autoencoders that embed and share the feature encodings of a sequence of interferograms, and then decode them to an estimation of their corresponding epochs. The autoencoders consist of convolutional LSTM (Long Short-Term Memory) cells that are trained on an InSAR dataset of a fixed size. First, in order to learn the general spatio-temporal structure of the dataset, a prior model is trained independently on overlapping sequences of 26 interferograms only (each made up of 9 epochs, covering 14 km by 12 km area on ground). We then successfully learn the temporal dependency when the weights of this model are used to initialize the succeeding model, which is trained iteratively by also...
considering features predicted in previous sequences. During testing, normal atmospheric signals are accurately reconstructed, while anomalies result in large residuals. The residuals are then passed to a detection algorithm that flags and estimates anomalous deformation.

To initially train and test our method, we use InSAR data from several Sentinel-1 tracks in Turkey, obtained from COMET’s LiCSAR processing system. Here we present our initial results, showing that our unsupervised and event-agnostic pipeline accurately detects both real and synthesized anomalous signals and recovers both the spatio-temporal structure of flagged deformation events and the time-series of non-deformation ‘nuisance’ signals. This new approach presents great promise for future automated analysis of large, global InSAR datasets, and for automated and robust separation of deformation from nuisance signals in InSAR data.