

Using deep learning to better image earthquakes

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Radar Interferometry (InSAR) is a techniques that can provide measurements of surface displacement from Space, with millimetric accuracy. These measurements are used in the natural hazards community, e.g. for earthquake analysis and landslide monitoring, and for monitoring anthropogenic activities, such as oil and gas extraction, and drawdown of underground water storage. A key step in the InSAR processing chain is that of phase unwrapping, which is the estimation of the integer ambiguities that are inherent with any measurement of phase. Although there are several existing algorithms that exist to do this automatically, they all generally fail when there is movement on faults at the surface, and visual inspection accompanied by manual correction is currently the only failsafe way to achieve this. Artificial Intelligence offers a novel way to solve this problem through the application of deep learning algorithms.

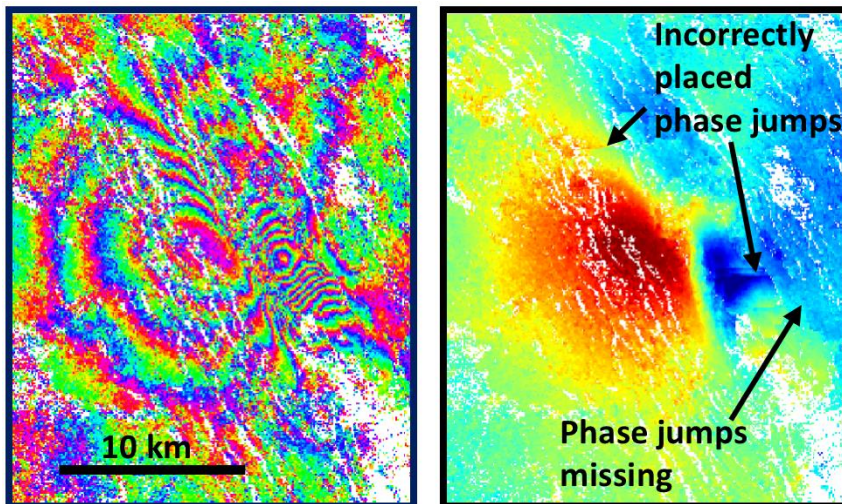


Figure 1. An interferogram showing deformation associated with the injection of magma and slip on faults in the Afar region of Ethiopia. Left is the original phase, where the coloured fringe represents contours of displacement, with each fringe indicating another 2.8 cm. The noisiest decorrelated pixels have been dropped. Right is the unwrapped version, representing eight phase cycles from red to blue (21 cm). Phase jumps are visible as sharp steps in colour

The nature of interferometry means that the phase in a radar interferogram only indicates the relative displacement of nearby pixels. Two pixels farther apart may have the same phase, but have undergone displacements that differ by any integer number of phase cycles (Figure 1). Before interpretation, the phase is usually “unwrapped”, which means integrating the phase gradient over the image to give the displacement of all pixels with respect to a reference pixel [Hooper and Zebker, 2007]. This is an ill-posed problem, with an infinite number of solutions that can fit the data. Further assumptions are therefore introduced, the most common of which involves minimising in some way, the number, or weighted sum, of “jumps” in phase between pixels of more than half a phase cycle [Chen and Zebker, 2001]. Accuracy can be improved further by unwrapping the phase of a time series of interferograms simultaneously [Hooper et al., 2007, Hussain et al., 2016]. In the case where there are no discontinuities in the deformation phase map itself, due to movement on faults that reach the surface for example, and the noise level is low, these algorithms can work well. Figure 1 shows an example where a state-of-the-art method

[Hooper 2010] does not succeed however; phase jumps (visible as a sharp step in colour) occur where they should not, and are missing where they are expected, along apparent fault lines that are visible in the wrapped image. In cases like this, errors are usually fixed by manual intervention. However, the fact that an expert can easily spot these errors by eye, suggests that a deep learning algorithm could be trained to achieve better results automatically.

Objectives:

Recent work on computing depth and surface orientation maps directly from single images is suggestive of an automated solution to unwrapping. Using deep networks with linked pipelines working at different spatial scales, the output maps are gradually refined, with information passing down from coarser to finer scales [Eigen and Fergus, 2015].

You will work with leading scientists at Leeds to:

- 1) Assemble a database of interferograms that have been correctly unwrapped with human assistance.
- 2) Generate simulated interferograms based on simple deformation models as a way of increasing the amount of training data available.
- 3) Develop a deep convolutional network, structured to produce an iterative spatial refinement, and trained on pairs of wrapped and unwrapped interferograms.
- 4) Apply the algorithm to real earthquakes as they occur and model the results.

Potential for high impact outcome

Almost every large earthquake throws up new unexpected details, which lead to new understanding of the underlying physics, published in high profile papers. Developing a method to can automatically unwrap the results for complicated ruptures will have a huge impact on the speed with which the data can be modelled, thereby contributing to high impact papers.

Training

You will work under the supervision of Prof. Andy Hooper within the School of Earth and Environmental Sciences, and Prof. David Hogg in the School of Computing. You will also become a member of the Centre for Observation and Modelling of Earthquakes, Volcanoes and Tectonics (COMET), which brings together experts from the Universities of Oxford, Cambridge, Leeds, Bristol, Reading, Liverpool and Newcastle and University College London (<http://comet.nerc.ac.uk>). Through COMET, you will have access to a range of training opportunities related to deformation monitoring and modelling, in addition to a broad spectrum of training workshops provided by the Faculty, from training in numerical modelling through to managing your degree and preparing for your viva (<http://www.emeskillstraining.leeds.ac.uk/>).

Student profile

The student should have a strong background in a quantitative science (e.g. computing, maths, physics, engineering, earth sciences) and an interest in earth sciences. Enthusiasm to develop new approaches to solving old problems is an advantage.

References

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