Applications of blind source separation for analysing volcanic deformation in satellite radar

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• ~340 measurements of magmatic and volcanic deformation

- Order of magnitude increase in availability and quality of SAR imagery
- Improved acquisition strategies and shorter repeat times
Global Volcano Programme Database, hosted by the Smithsonian Institution. Jennifer Jay, Matt Pritchard, Maria Furtney, Ben Andrews, Ed Venzke

COMET catalogue: Susanna Ebmeier, Juliet Biggs, Amy Parker, James Hickey, David Arnold, Ryan Lloyd & Elspeth Robertson
• **Additions** presented: (1) displacement signal area & rate interpreted: (2) depth & distance from volcano

• Higher proportion of InSAR measurements capture non-magmatic and non-eruptive processes than ground based measurements
Ebmeier et al., under review
• Multiple deformation sources at the same volcano & multiple cycles of deformation

• Source location ≠ reservoir location: elastic deformation can be caused by volume changes in different parts of a reservoir

• The relationship between distinct deformation sources provides information about processes within a magmatic zone
  - mechanisms for melt or volatile movement
  - local response to stress changes
Methods for separating volcanic signals from each other and from noise

Assumptions

1. A priori knowledge of signal that signal has been observed before
2. Increasing signal to noise ratio displacement has constant rate
3. Filtering (spatial or temporal) signal and noise have different magnitudes
4. Blind source separation signal characteristics only
1. Separation of signals caused by different processes

2. Test of signal significance

Independent Component Analysis

Inter-group cluster analysis
fMRI resting state networks, Beckmann & Smith, 2004

High temperature events from SEVIRI, Barnie & Oppenheimer, Remote Sensing, 2015

Widely applied in medical physics, signal processing and other branches of remote sensing
Independence is assessed using kurtosis or approximation of negentropy.

- Decomposition performed with FastICA algorithm

**Preparation:**
- centring & whitening
- dimension reduction using PCA
- iterative correction of choice of dimensions
Interferograms are linear combinations of phase changes with different origins

atmospheric changes, change in satellite position & Earth surface displacement
• Each pixel in an interferogram is a linear combination of points from several time series.

• We assume that an interferogram is closer to a Gaussian distribution than all (most) of the signals that make it up.
Assume that signals of interest are spatially independent

\[
\mathbf{X} = \mathbf{A} \mathbf{S}
\]

Rows of mixing matrix record the contribution of a source to each interferogram

Sources maximise the independence of spatial patterns
Assume that signals of interest are spatially independent

- Independent components and mixing matrix rows are ambiguous
- Order of independent components in Source matrix is not significant
- Spatial or temporal filtering can be applied to interferograms before decomposition
- sources identified as separate components
- contribution to each interferogram recorded in mixing matrix
• signal reconstructed from only components of interest (with some noise)

• independent synthetic deformation sources are separated from each other, and from the atmospheric noise

• for these synthetic data, sources were separated at signal to noise ratio as low as ~0.1
Identifying significant sources

Cluster Analysis performed on two independent groups of data

• spatial patterns that capture a real property of the data appear in both groups and will be assigned to a cluster.

• Groups can be:

1. different time periods
2. the same time periods but independent groups of images

Clusters identified using ISCTEST algorithm

Hyvärinen & Ramkumar, 2013
**Volcán Calbuco, Chile**

- Calbuco erupted on 22 April 2015, 43 years after its last recorded activity.

- VEI 4, 17 km a.s.l. plume.

- No pre-eruptive deformation evident in Sentinel-1 interferograms.

*Figure 3.*

- Subsidence captured by three Sentinel-1 tracks, consistent with subsidence during first phase of eruption with a source ~13 km depth.

*by Marco Bagnardi, from Pyle et al., in prep*

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**Expected mixing matrix**

Interferogram number / time

Source contribution

eruption
• Component that represents deformation can be identified from mixing matrix, given time of event alone

• End member test -> separation of subsidence and atmospheric features most difficult where deformation appears in > 1 interferogram
Deformation and atmospheric features are separated without any a priori information.

Isolation of deformation from atmospheric signals also successful using the assumption of time independence …. but dimension estimation and computation is much harder.
Parícutin lava fields

- Monogenetic eruption in 1943-1952 -> cinder cone and lava fields 100s of metres thick

- Lava subsidence well constrained by InSAR studies: *Fournier et al., 2010; Chaussard, 2016*

- Expectation: three patches of subsidence retrieved in the same component
- Three patches of deformation extracted in one spatial component
  - > implies that source is the same

- Subsidence rates with error of previous ALOS measurements:
  \[ 5.3 \pm 0.5 \text{ cm/yr} \], compared to 5.5 cm/yr 2007-10
Considerations for testing the independence of volcanic deformation signals:

1. Components/mixing matrices retrieved from spatial and temporal ICA can be compared to test their significance.
2. Amendments can be made to decomposition procedure to test for correlated signals that are temporally offset from each other.
3. How should we interpret evidence of spatial/temporal correlation?
Considerations for identifying deformation and for automation

1. How are ‘relevant’ signals identified?
   - *a priori* information about signal shape or duration
   - matching ICs to past deformation (machine learning?)

2. What resolution to apply analysis?
   - Need to know past spatial and temporal scales
   - Nested approach, with higher resolution over active volcanoes

3. Regional or local application?
   - Implications for Gaussianity of some components
   - Size of co-variance matrix
   - Statistical independence depends on spatial scale
Further details of method and tests with synthetic data:

**Journal of Geophysical Research: Solid Earth**

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**Key Points:**
- Independent component analysis is appropriate for exploratory analysis of InSAR data
- Deformation can be identified automatically by cluster analysis of independent components
- Application of ICA demonstrated on Sentinel-1A imagery using contrasting volcanic examples

**Application of independent component analysis to multitemporal InSAR data with volcanic case studies**

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**Abstract** A challenge in the analysis of multitemporal interferometric synthetic aperture radar (InSAR) data is distinguishing and separating volcanic, tectonic, and anthropogenic displacements from each other and from atmospheric or orbital noise. Independent component analysis (ICA) is a method for decomposing a