Using independent component analysis (ICA) with time series of InSAR data to monitor volcanoes

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Why automate the detection of volcanic unrest with Sentinel-1 InSAR data?



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Previous results: isolating large deformation and detecting changes in rate



Image: Google Earth

- Increase the variance of deformation signals to recover them.
- Apply ICA temporally at stratovolcanoes.
- Visualise status for large number of volcanoes (using deep learning).
- Apply globally by implementing on JASMIN computing system



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• Create a network of interferograms that maximises deformation variance.

Deformation





- Use ICs (latent sources) from ICA step.
- Take a baseline stage of 1-2 years.
- Invert to fit each interferogram using ICs
- Record residual of fit.
- Fit linear trend through IC time courses and residual.
- Run monitoring.



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 time course of IC0.
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- How independent are signals in time/space?
- How many samples do we have in space (pixels) vs in time (acquisitions)?
- Synthetic example where we vary the spatial independence.
 - \rightarrow Non-overlapping (independent) signals work well with sICA.
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• Modified from Gaddes et al., 2018

LiCSAlert: temporal ICA at Vesuvius

- In 2018, ~100 acquisitions, but now ~300.
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(Near) global application: results

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- Condense our LiCSAlert figure into 2 values: \rightarrow Changes in existing deformation
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- But, we have to first identify deformation source.

 \rightarrow Use deep learning (CNN):

 \rightarrow Red: model predictions, black: human label:

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WxH (km): 26 x 42 DEM (m): (0, 1121) 20151114 20170718 0.767 m -10 -91.04 -91.28° -0.62 8 Sigma for new def. 20170531 20170718 0.0797 m 6 -1.0 0.0 4 С 0 ٠. -0.5 2 ٠ 0.00 υ 0 0 -0.05Sigma for exising def. 0.2 IC 2 , C 0.0 0.025 СЗ 0.000 -0.025RMS 0.002 RMS m trend line 0.50 0.000 IC (m) - 0.25 20110102 2016/07/07 2017/01/01 2016/01/07 ^{2016/08/07} 2016/2010, 2017/08/07 0.00 -0.25 Date

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Visualising the status: ~500 volcanoes, 1 time

• Applied to ~1500 LiCSAR frames

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- Improve the quality of our LiCSBAS time series (collaborate with the COMET Volcanic and Magmatic Deformation Portal backend data?).
- Web-based interactive LiCSAlert figure (possibly on COMET Volcano Portal).
- Community use/feedback from case studies the code is on GitHub!

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Pinned	Customize your pins
UolcNet Public #	UDLNet_21 Public #
A database of labelled Sentinel-1 data featuring examples of volcanic unrest.	Volcanic Unrest Detection and Localisation Net 2021: A CNN that is able to detect and localise deformation in Sentinel-1 unwrapped interferograms.
🔵 Python 🏠 4 😵 3	● Python ☆4 ¥3
LiCSAlert Public ::	SyInterferoPy Public #
Volcano monitoring using Sentinel-1 InSAR data	Generate synthetic interferograms that are similar to those produced by the Sentinel-1 satellites.
● Python 🟠 15 😵 2	● Python ☆ 18 약 6
	SRTM-DEM-tools (Public)
An algorithm for robustly appling sICA to InSAR data	Tools for making and manipulating SRTM1 and SRTM3 Dems.
● Python ☆ 32 学 5	● Python 🕁 2 😵 3

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- Networks that increase the variance of deformation signals are needed when using sICA at most volcanoes.
- At stratovolcanoes, tICA outperforms sICA.
- LiCSAlert is able to detect subtle changes in deformation rate (e.g. Campi Flegrei).
- LiCSAlert is able to detect when new deformation enters a time series (e.g. Erta Ale, La Palma).
- Using deep learning to identify the deformation source allows us to condense much of a LiCSAlert figure into a simple 2D plot.

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