Deep Learning–Based Mitigation of Atmospheric Noise in InSAR Unwrapped Phase Maps

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Outstanding Student & PhD candidate Presentation contest

1. Introduction

➢ **Background**

InSAR is a powerful tool for measuring ground deformation with high precision (cm-level).

➢ **Problem**

However, InSAR results are often contaminated by **atmospheric** and **ionospheric noise**.

➢ **Research gaps for the current method**

Existing correction methods usually rely on **external datasets**, which limits their general applicability.

➢ **Motivation**

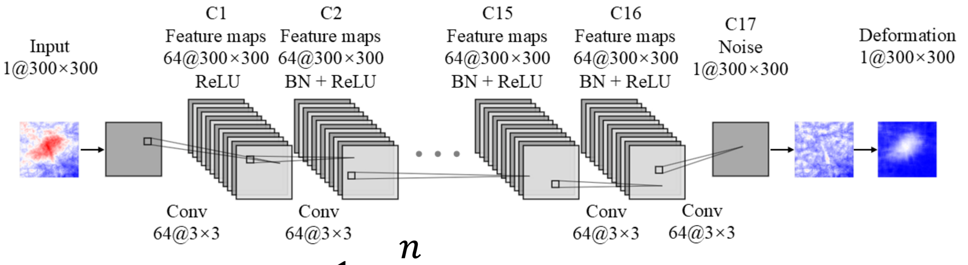
Therefore, this study aims to develop an **efficient deep learning** method for noise reduction without external data.

2. Methods

➢ A modified supervised Denoising Convolutional Neural Network (**DnCNN,** Zhang K et al., 2017)

➢ **Residual learning** (He K et al., 2015) enables efficient denoising while preserving deformation signals.

➢ All model training was conducted on an NVIDIA RTX 3090 GPU.



$$l(\theta) = \frac{1}{2n}\sum_{i=1}^{n}\|R(y,\theta) - (y - x)\|^2$$

➢ $l(\theta)$: Average loss of a batch
➢ n: Batch size
➢ y: Noisy InSAR input maps
➢ x: Reference maps

3. Training, validation, and testing

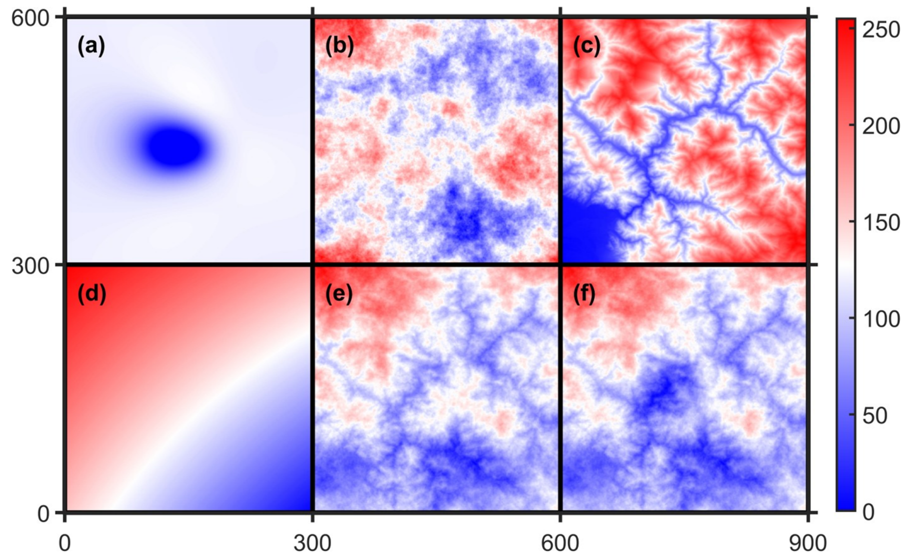
A Synthetic Data

➢ **HGPT model**

ERA5-Based Hourly Global Pressure and Temperature model (Mateus et al., 2020)

➢ **ITD method**

Iterative Tropospheric Decomposition method (Yu C et al., 2017)



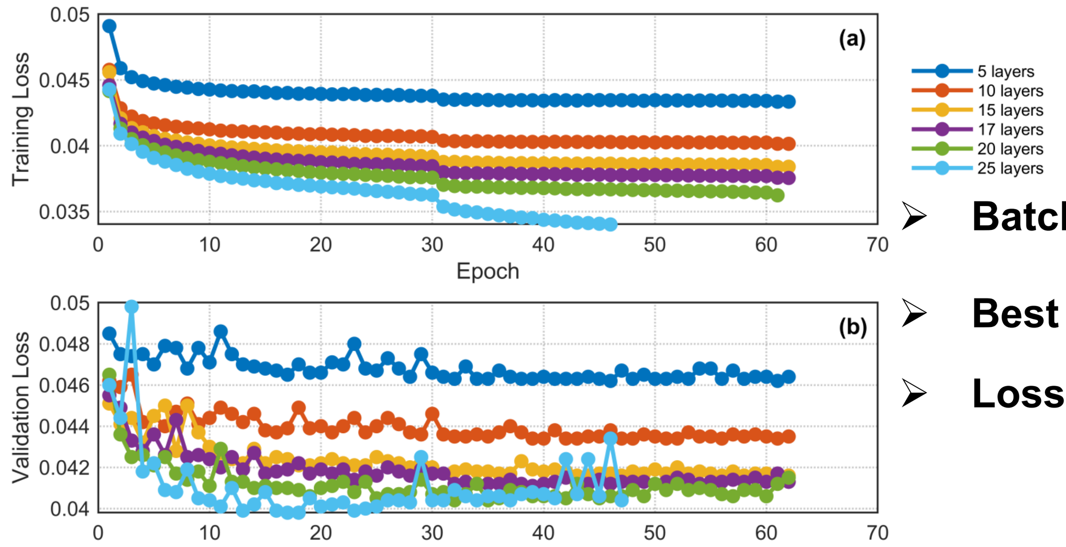
➢ **Normalization**

- Each synthetic sample was generated as a 300 × 300 image with a pixel spacing of 5.5 arcsec and normalized to 8-bit values (0–255) for training.

➢ **Components of synthetic data**

- (a): **reference maps**, Okada85 (rectangular fault) and Mogi source (point inflation/deflation source)
- (b)-(d): **noise components** — correlated noise, stratified delay, bilinear ramp (Stratified delay: HGPT + ITD)
- (e): **reference residuals**, (b) + (c) + (d) = (e)
- (f): **Synthetic LOS input maps**: (a) + w*(e) = (f), where the weight factor w varies from 0.6 to 1.2.

B Training and validation



➢ **Batch size**: 64

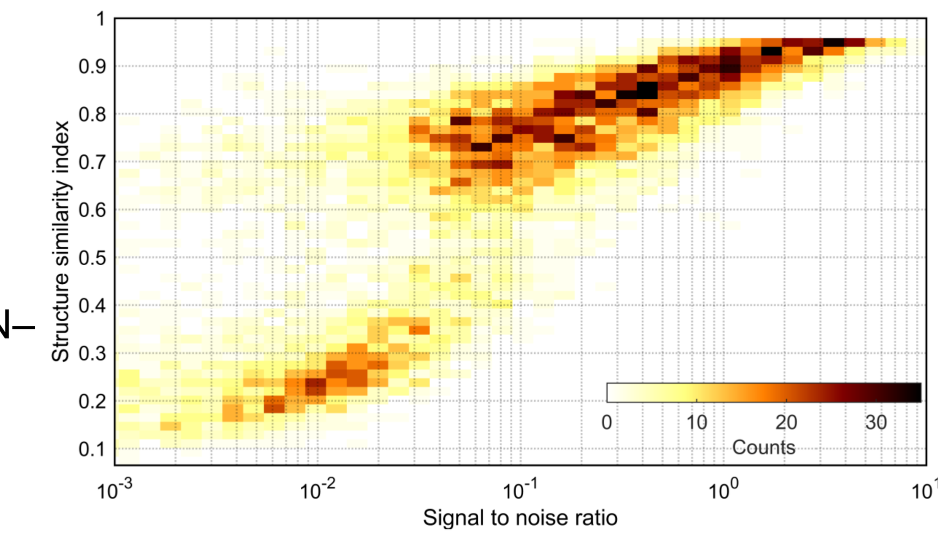
➢ **Best depth**: 20 layers

➢ **Loss**: L2 residual loss

➢ **Datasets**

- Training: 30,000 from [54°E–120°E, 26°N–37°N]
- Validation: 1,500 samples from [100°W–120°W, 37°N–46°N]
- The latitude/longitude ranges indicate the geographic regions used to generate the synthetic training and validation datasets.

C Testing



➢ **Datasets**

- Testing: 7,000 samples, from [70°E–110°E, 40°N–50°N]

➢ The test shows that the model performs stably under moderate-to-high SNR conditions, while **performance degrades when SNR decreases to between 1e−1 and 1e−2.**

$$SSIM = \frac{2\mu_x\mu_x'}{\mu_x^2\mu_{x'}^2} \times \frac{2\sigma_x\sigma_x'}{\sigma_x^2 + \sigma_{x'}^2}$$

$$SNR = \frac{P_x^2}{P_{y-x}^2}$$

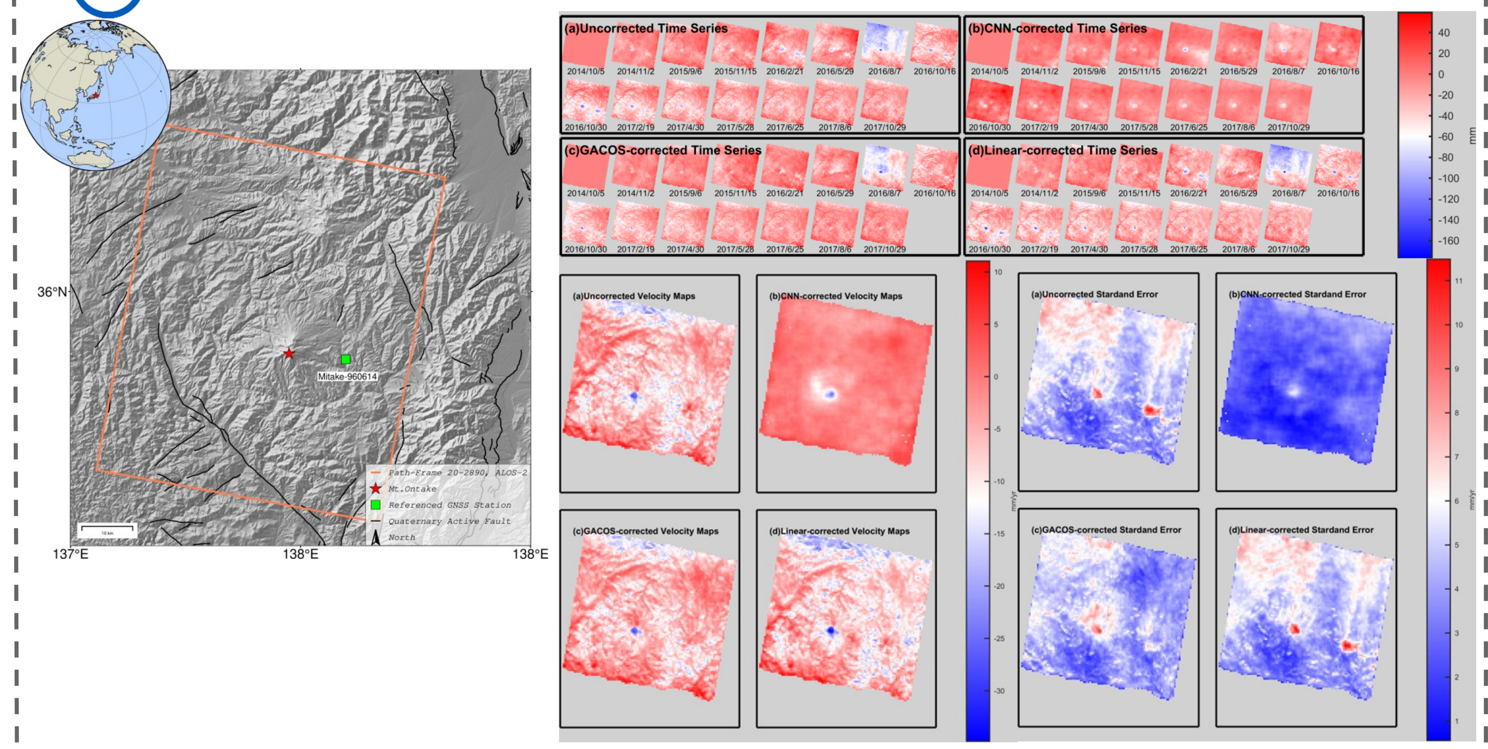
μ_x, μ_x': mean of the reference maps and estimated reference

σ_x, σ_x': standard deviation of the reference maps and estimated reference

p_x, p_{y-x}: power of reference maps and reference residuals.

4. Results

A Case study of Mt. Ontake volcano, Japan



➢ **Dataset/background**

- 2014.10–2017.10
- 15 ALOS-2 time series
- September 2014 eruption

➢ **Velocity comparison at the red-star location**

- Uncorrected: -23.82 ± 7.75 mm/yr
- GACOS-corrected: -24.50 ± 8.03 mm/yr
- Linear-corrected: -30.81 ± 8.29 mm/yr
- CNN-corrected: -29.95 ± 5.21 mm/yr

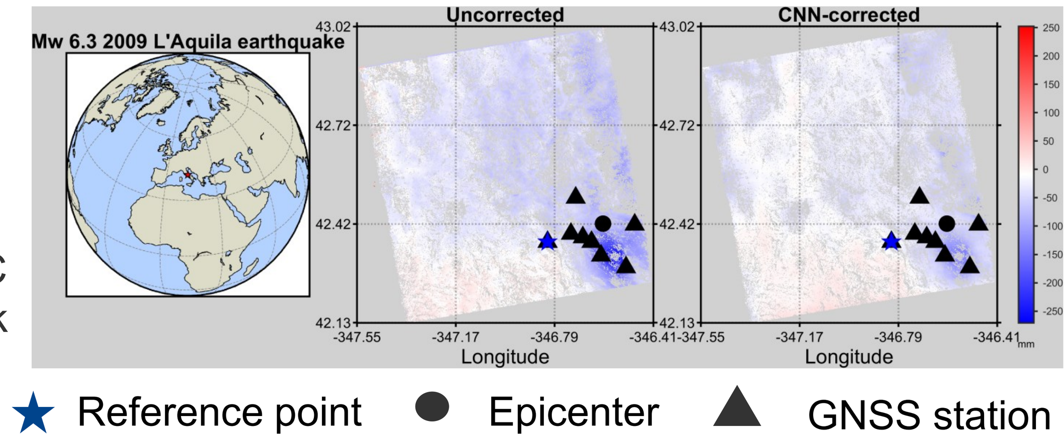
➢ **Main result**

- **The CNN-corrected result shows the lowest velocity uncertainty.**

B Case study of the 2009 Mw 6.3 L'Aquila earthquake

➢ **Dataset/background**

- 2008.07–2009.04
- One pair of ALOS SLC
- 2009.04.06 Mainshock



➢ **Comparison with previous study**

- **Comparison with 8 continuous GNSS sites in LOS direction**
- GNSS displacements are from Anzidei M et al., 2009

Name	GNSS LOS (mm)	Uncorrected (mm)	CNN-corrected (mm)
AQUI	-64.6 ± 15.2	-102.6	-54.3
CADO	-102.6 ± 19.3	-147.7	-143.0
CPAG	-0.4 ± 18.4	-47.4	-13.8
INGP	-34.4 ± 15.5	-57.3	-34.5
INFN	-22.5 ± 15.2	-80.0	-45.4
ROIO	-113.5 ± 16.0	-164.2	-94.7
SELL	0.0 ± 0.0	0.0	0.0
SMCO	-3.3 ± 14.8	-32.8	-5.0

➢ **Main result**

- The CNN-corrected LOS displacements **better agree with the GNSS observations, reducing GNSS–InSAR L2 misfit by 53.5%.**
- The **overall standard deviation decreases** from 31.58 mm to 23.94 mm.

5. Discussion and Future Work

➢ **Discussion**

- **Strengths**
  - No external datasets required
  - Applicable to volcanic and tectonic InSAR cases
- **Implications**
  - Lower uncertainty after CNN correction
  - Better agreement with GNSS observations after CNN correction
- **Constraints**
  - Dependence on synthetic training data
  - Performance degrades under very low-SNR conditions
  - Sensitivity to low-coherence areas and outliers

➢ **Future work**

- Separating noise directly from real InSAR data and further improving the model using more advanced neural network architectures with residual learning.

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