FAST AND ACCURATE SUB-PIXEL DISPLACEMENT ESTIMATION FROM OPTICAL SATELLITE IMAGES USING A NEW HYPER-REALISTIC EARTHQUAKE DATABASE AND U-NET ARCHITECTURE

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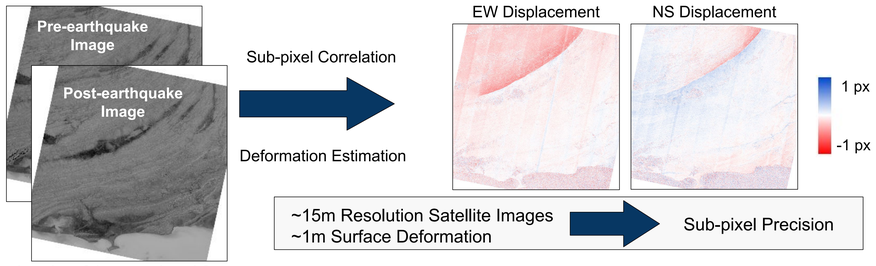
INTRODUCTION

Objectives of Sub-pixel Optical Image Correlation



Landsat 8 images, band 8
15k x 15k pixels

TRADITIONAL OPTICAL CORRELATION APPROACHES

- **Iterative phase correlation method** with frequency masking, ex. **COSI-Corr [2]**
- **Spatial Cross Correlation, MicMac [3]**

… are **limited** by different noises:
- Differences in the illumination conditions
- Temporal changes (vegetation, etc.)
- They also are rather **slow**.

DATA-DRIVEN APPROACHES

- **Convolutional Neural Networks (CNN): Our previous work [4]** predicts 1 displacement vector at a time
- **U-net CNNs (e.g. Optical Flow DL [5]), never tested, could** predict the regional flow

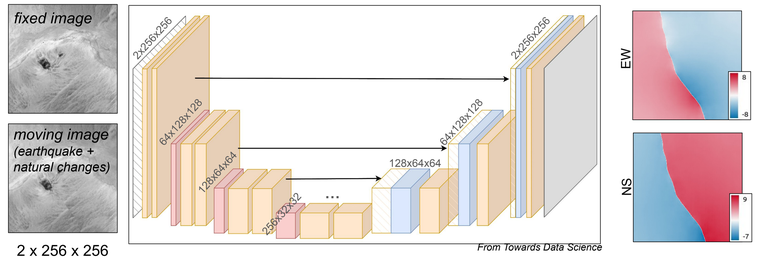
… have the potential to **attenuate / overcome** some limitations by **learning to correct** biases

- a **pixel-based CNN** can tackle a specific noise (ex. **discontinuities [4]**), but **can't learn the spatial context.**

→ Can an optical flow model, such as FlowNet [5], be effective for sub-pixel displacement estimation?

→ How to collect a specific labelled database for training?

U-NET MODEL AND TRAINING



Architecture from Flownet2 **[6]** : **Flownet-SD**

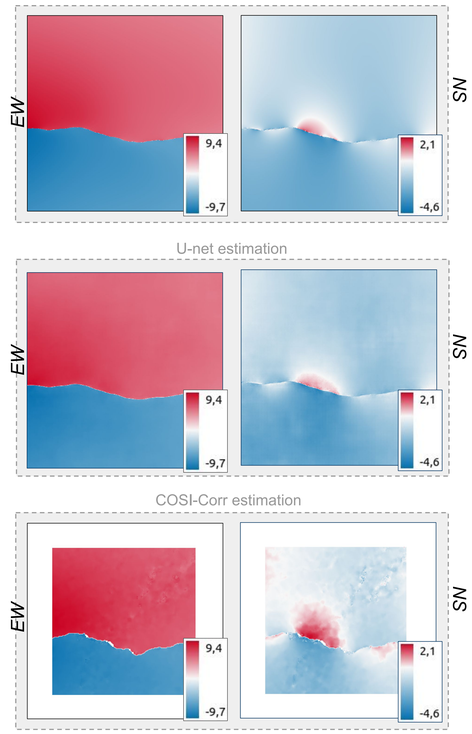
❖ **Model:**
- ➢ applied as a **sliding window** of size 512x512 px on a full satellite image pair, where the "post-image" contains a deformation
- ➢ *Flownet-SD* : succession of 3x3 conv. layers and LeakyReLU for the contracting part (left) and of deconv. layers and activation functions for the upscaling part (right).

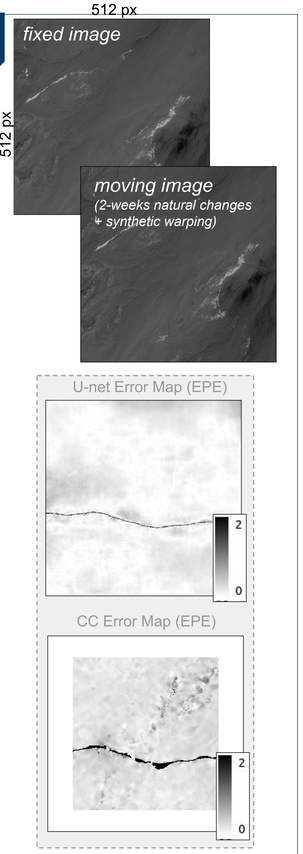
❖ **Loss**: Endpoint error (**EPE**): $\|V_{est} - V_{gt}\|$
- ➢ Euclidean distance between the *predicted flow vector* and the *ground truth flow vector*, averaged over all pixels.
- ➢ **multi-scale EPE:** computed at different scales of the model

over 100 test 512x512 samples	**mean EPE**
Ours	**0.23px**
COSI-Corr	0.26px

❖ **Computation time:** *1 GPU Nvidia Tesla V100 SXM2 32 Go*
- ➢ **Training** on 36 000 samples, 50 epochs: one **epoch** takes **447s**.
- ➢ **Inference** :
End-to-end sliding window pipeline on real Pleiades images ***22976 x 19782 pixels****, of res. 50cm, takes* ***100.9s*** *(stride of 1)*
COSI-Corr*, with a 32x32 pixels sliding window with stride=4 (optimal standard configuration), takes* ***180s*** *using 64 CPU cores.*

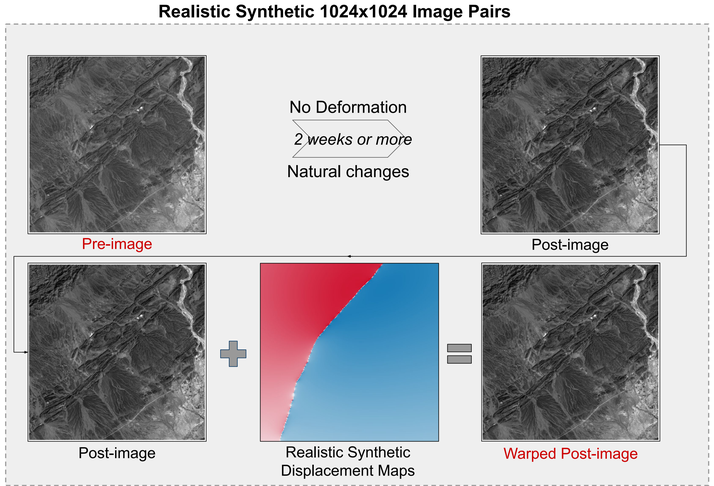
QUALITATIVE RESULTS



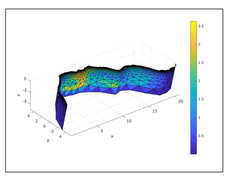


SYNTHETIC DATABASE GENERATION

Realistic Synthetic 1024x1024 Image Pairs

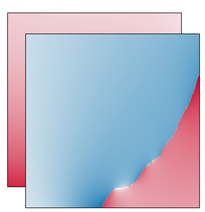


How to generate realistic synthetic displacement maps?



- **Realistic fault** (mesh in 3D) with fractal slip distributions and realistic geometric roughness
- Associate a random **strike-slip dislocation** *(random size, location, depth, direction…)*
- Estimate the **cumulative displacement** everywhere with **triangular displacement elements** (TDEs), sub-pixel resolution at the surface using *Cutde* software.

How to warp with sub-pixel precision?

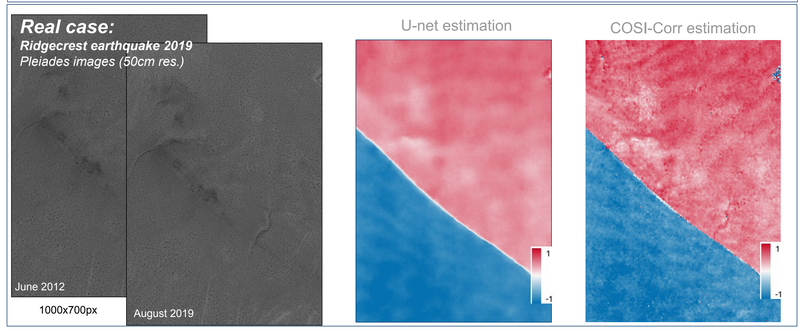


- Extract **1024x1024 Landsat-8 panchromatic images** at 2 different dates on **stable regions** (no ground deformation occurred)
- Keep only the pairs for which the mean correlation is higher than 0.9
- Warp the second (post) image with **quintic-order spline re-sampling** algorithm (precision: 1/100th of pixel)

10k faults + 10 locations - **2k faults + 2 locations** - **2k faults + 2 locations**

90k training samples - 18k validation samples - 18k test samples **x 4 scaling factor ranges**

This ultra-realistic dataset will be freely released.
It can be used for training, evaluation and comparisons of new methods with state-of-the-art.



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CONTACT

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