SUB-PIXEL OPTICAL SATELLITE IMAGE REGISTRATION FOR GROUND DEFORMATION USING DEEP LEARNING

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ABSTRACT

Precise estimation of ground displacement at regional scales from optical satellite imagery is fundamental for the study of natural disasters, such as earthquakes, volcanoes, landslides, etc. Current methods make use of correlation techniques between two acquisitions in order to retrieve a fractional pixel shift. However, differences in local lighting conditions between two acquisitions can lead to differences in image reflectance, which in turn can bias the displacement estimate, especially in the sub-pixel domain. Data-driven methods may provide a way to overcome these errors. From the generation of a realistic simulated database based on Landsat-8 satellite image pairs with added simulated sub-pixel shifts, we developed a Convolutional Neural Network (CNN) able to retrieve sub-pixel displacements.

Index Terms— optical image correlation, image registration, satellite imagery, deep learning, geodesy

1. INTRODUCTION

Image registration is a key operation in image processing with applications across different domains, such as computer vision, biomedical imaging, and remote sensing [1]. Focusing on the latter, Digital Image Correlation (DIC) has revolutionized satellite geodesy and particularly the study of ground deformation related to natural hazards such as earthquakes. DIC is used to retrieve displacements fields between two images acquired on two different dates (separated by days, weeks, months, or even years). The use of optical satellite images is particularly efficient for capturing ground displacement over very large regions in a quick, cheap, and efficient way. However, this task is relatively challenging, as ground displacements are largely in the sub-pixel domain; earthquake surface displacements are generally several meters at most, and are similar in magnitude to the resolution of freely available optical satellite datasets typically used in Earth Observation (e.g. Landsat-8: 15 m, Sentinel-2: 10 m).

Current remote sensing sub-pixel registration methods rely on a sliding window approach, by assuming a simple uniform 2D shift at a local scale. Image registration is typically undertaken in the spatial domain, or the frequency domain [2, 3, 4]. Local spatial cross-correlation coupled with SINC-based resampling, non-linear cost-functions, and spatial regularization [5] has been implemented in the open-source MicMac software [6]. It allows a robust correlation calculation with small correlation windows, providing high spatial detail. However, this approach can be computationally expensive. Phase correlation for sub-pixel registration [7] is another efficient technique, based on the Fourier shift theorem. The relative displacement between two images is estimated from the phase difference of their Fourier transforms [8]. Splitting the sub-pixel problem into two steps (pixel-wise displacement estimation, followed by sub-pixel displacement estimation, using a minimization algorithm) is an efficient approach that has been developed in the COSI-Corr software package [9]. Phase correlation works well with large correlation windows, but is less satisfactory when using smaller correlation windows (due to increased sensitivity to high frequency noise). Therefore, phase correlation may be less suitable for obtaining spatial detail compared with more robust spatial domain methods.

Image registration and displacement field estimation have been successfully addressed by data-based methods and particularly Deep Learning (DL) models, e.g. in the field of medical-imaging [10], video surveillance, robotics, and self-driving systems [11]). The advantages of DL are that it exploits the large amount of available data, as well as its particular structure (such as Convolutional Neural Networks (CNN) for image-like data). Most of the work in DL applied to image registration is based on optical flow, such as the model FlowNet [12], or using CNNs to estimate the motion of objects. The large majority of registration problems involve es-

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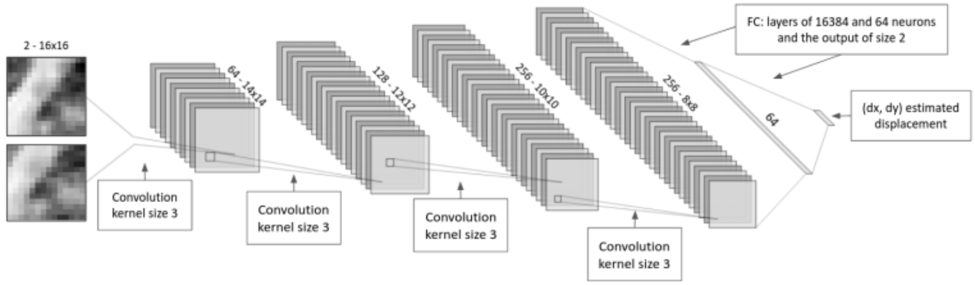


Fig. 1: The proposed CNN model for sub-pixel shift estimation from pairs of remote sensing windows.

timating large displacements (> 1 pixel), while the estimation of sub-pixel shifts has been less studied. In the field of material science, recent experiments using DL to retrieve sub-pixel displacement and/or strain fields [13, 14] have been conducted on speckle images, demonstrating the feasibility of data-based approaches for sub-pixel measurements. However, both the data, and particular issues in remote sensing (such as differences in illumination and surface change) are substantially different, so these tools cannot be used directly.

Based on the promising application of DL in similar domains, we propose, for the first time (to the best of our knowledge), a DL solution for ground deformation estimation using remotely sensed optical satellite images. In this preliminary study, we develop a specific CNN to reproduce a correlator that estimates sub-pixel surface displacements (e.g. for an area subject to a ground motion, e.g. an earthquake), using satellite imagery. We formulate the problem as a uniform shift between a pair of tiles and estimate the 2D displacement for each window independently, similar to current state of the art correlator methods [9, 6]. This proposed method has the potential to overcome issues related to image differences due to different image acquisition times (differences in illumination conditions can bias the correlation [15], leading to registration inaccuracies correlated with topography, etc). One major contribution of this work is the development of synthetic databases with real acquisitions and simulated sub-pixel shifts. Once trained on our datasets, our model is applied on a distinct pair of satellite images using a sliding window process in order to infer the complete displacement map. We compare different models by varying the training database settings and evaluate the precision of the estimated shifts. A complete comparison with a phase cross correlation method [16] and with a state-of-the-art correlation tool optimized for retrieving earthquake ground displacements (COSI-Corr [9]) is performed on a realistic earthquake experimental dataset.

2. METHODOLOGY

2.1. Problem statement

We consider two windows W_1 and W_2 linked by a rigid 2D translation (d_x, d_y). The image registration problem using traditional correlation is solved by identifying a translation vector $(\hat{d_x}, \hat{d_y})$ such that the correspondence between $W_1(x, y)$ and $W_2(x + \hat{d_x}, y + \hat{d_y})$ is maximized (according to some measure of correspondence). The shift between the two images can be addressed by finding

$$(\hat{d_x}, \hat{d_y}) = \text{argmax}_{(d_x,d_y)}\, r\left(I_1(x, y), I_2(x + d_x, y + d_y)\right),$$

in which r refers to cross-correlation. In this work, we consider a regression problem at a local scale, using a data-driven approach, in which $(\hat{d_x}, \hat{d_y}) = \hat{f}(W_1, W_2)$, where f is a function learned from a set of N reference training data $\{X_n; Y_n\}_{n=1}^{N}$ with $X_n = (W_1, W_2)_n$ and $Y_n = (d_x, d_y)_n$ such that

$$\hat{f} = \text{argmin}_f\, \mathcal{L}\left(f(X_n), Y_n\right),$$

with $\mathcal{L}(\cdot, \cdot)$ being a function computing the loss between the displacement estimated by a regressor f and the reference displacement (here taken as the mean squared error). The proposed approach is to approximate a rigid and non-rotating transformation, by evaluating the displacement (dx, dy) for every image patch of size $k \times k$ (with k the size of the correlation window in pixels).

2.2. Extraction of a rigid 2D shift with a Convolutional Neural Network (CNN)

In this work, a CNN is used to retrieve this bi-directional displacement. Figure 1 gives an overview of the architecture of the network performing the correlation. As input, the model processes a pair of windows of size $k \times k = 16 \times 16$ pixels. This size of window provides a sufficient number of data (pixels) for the model to retrieve the shift, yet small enough to give a relatively good spatial resolution. This pair represents a pre- and post-event window spanning a source of ground deformation (such as an earthquake). For the architecture, convolutional layers are used to extract feature maps, and to reduce the size of the data (as the window is small and no padding was used). Four layers using an increasing number of 3×3 kernels are used (see Figure 1 for details). The chosen hyper-parameters represent a trade-off between computation time and accuracy. Tests were also made with smaller architectures, with smaller number of layers, and kernels per layer. Decreasing the number of kernels and layers does limit the accuracy, yet decreases the operation cost. These two hyper-parameters have been chosen more to maintain a good precision and accuracy of the model rather than reduce computation time. Based on our experiments, increasing the number of feature maps per layer instead of increasing the number of layers is more valuable, and going above four layers does not improve the results. The size of the kernels 3×3 was selected in order to extract small features in already small 16×16 windows. A Fully Connected (FC) layer is attached after this structure, to output a vector (two values) representing the shift in two directions (horizontal and vertical).

2.3. Synthetic data generation

As we use a supervised machine learning approach, a reliable training set for learning the image registration operator is required. As too few datasets with real images and reference displacements are available, we create realistic synthetic data for this process. We define two windows W_1 and W_2, taken at two different dates t_1 and t_2. We consider a synthetic displacement field $D : R^2 \to R^2$ with $D(x, y) = (d_x, d_y)$ with $(d_x, d_y) \in [-1, 1]^2$. In order to simulate a uniform shift, a 2D translation on every window is artificially applied, by cropping the window shifted by a fraction of a pixel in row and column (giving a 2D synthetic offset), from the larger satellite image. A re-sampling algorithm is necessary, because the shift is sub-pixel. In this process, the Lanczos 6×6 kernel size [17] is used for the interpolation. This way, we can incorporate a uniform synthetic displacement field $D(x, y)$ in a pair of windows. Three different training datasets are created and standardized (re-scaled with a 0-mean and a unit variance) from real Landsat-8 acquisitions, in order to evaluate which type of data allows the model to reach the highest accuracy (see Table 1):

No noise dataset (NN dataset): pairs of windows are built from the same satellite image. We apply a random shift on all of the samples. We have: $W_{2,\mathrm{NN}}(x, y) = W_1(x + d_x, y + d_y)$;

Synthetic noise dataset (SN dataset): pairs of windows are built from the same image, but a synthetic Gaussian noise is added within the second image. Similarly, we applied a random shift on the samples. We have: $W_{2,\mathrm{SN}}(x, y) = W_1(x + d_x, y + d_y) + U(x, y)$, where $U(x, y)$ is uniform random noise with a dynamic range consistent with the global image;

Difference in Acquisition Time dataset (DATe dataset): pairs of windows of the same area are taken at different acquisition times; prior co-registration of satellite images is required, which is the case with Landsat-8. This allows us to create samples containing realistic perturbations in illumination, vegetation, etc. Random sub-pixel shifts were applied on all samples. We have $W_{2,\mathrm{DATe}}(x, y) = g_{\Delta t}(W_1(x, y))(x + d_x, y + d_y)$ with g the natural evolution of the ground acquisition during Δt.

Dataset	Noise	Δt Acquisition time difference	Nb samples train	eval.
NN	0	0	80000	20000
SN	Gaussian	0	80000	20000
DATe	”Real”	1 to 48 months	80000	20000

Table 1: Description of the datasets used to train and evaluate the model.

The CNN model is trained with each dataset separately. Therefore, three distinctly trained models are evaluated and compared to the phase cross correlation (PCC) method from the scikit-image library. The evaluation is made on similar Landsat-8 data to that used in training, albeit acquired on different dates and locations, to guarantee that there is no common data used in both training and evaluation processes.

3. RESULTS

3.1. Evaluation of the models

We use Mean Average Error (MAE) to compare the precision of the outputs of the models and the PCC method. This criterion evaluates the absolute difference between the prediction and the true value of the shift vector (in pixels).

	NN dataset	SN dataset	DATe dataset
PCC	0.23	0.22	0.29
CNN-NN	**0.022**	0.095	0.14
CNN-SN	0.039	**0.057**	0.12
CNN-DATe	0.036	0.063	**0.095**

Table 2: Mean absolute error (in pixels) on the NN, SN and DATe evaluation datasets, for the PCC and the CNN models.

Table 2 compares the CNN models and PCC, evaluated on NN, SN and DATe test datasets. The table shows that our method is able to retrieve accurate displacements vectors. The model giving the best mean results (i.e. most accurate across all three datasets), with the lowest MAE on the most realistic data (DATe dataset) is the CNN-DATe. This model has been selected for the following evaluations on larger images.

3.2. Results on realistic synthetic regional data

A second validation addresses an effective way to evaluate the precision of our CNN-DATe by comparing it against PCC and COSI-Corr on a test case using Landsat-8 satellite images re-sampled to include a realistic synthetic offset.

We developed an algorithm that computes synthetic surface displacements for randomly generated realistic fault discontinuities with rough (fractal) geometries and slip distributions embedded in a homogeneous elastic halfspace [18]. These displacement fields $D(x, y)$ are used to warp satellite images using a quintic spline re-sampling algorithm [19]. Here, $D(x, y)$ is now not uniform, as it describes a realistic fault displacement, and the warped satellite images are larger ($k = 1024$). The input images and synthetic displacement maps (EW and NS) are given in Figure 2. We apply the different models, CNN-DATe, PCC and COSI-Corr as a sliding 16×16 window to obtain the large-scale displacement maps (COSI-Corr uses a 32×32 window, although the effective width is 16×16, due to the windowing function applied [20]) .

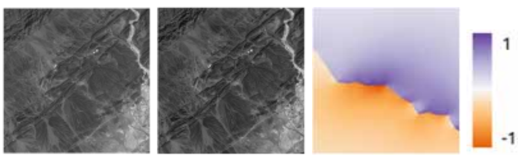
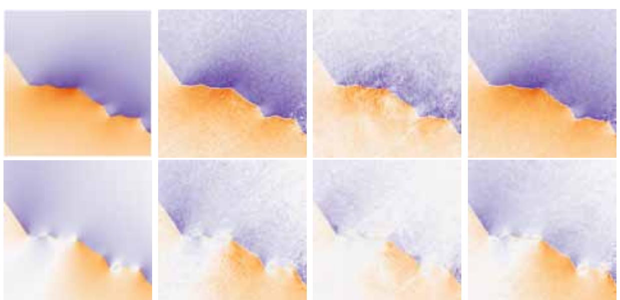


Fig. 2: Pre-image (left) and post-image (center) warped with the synthetic displacement map (right, EW, in px)



(a) (b) (c) (d)

Fig. 3: Synthetic displacement map (a), with CNN-DATe (b), PCC (c), and COSI-Corr (d) displacement maps, EW and NS components (same scale as Fig. 2)

From Figure 3, all three methods recover the first-order features of the input synthetic displacement maps. However, when the correlation window straddles the discontinuity (representing the earthquake ground rupture), the assumption of a simple 2D translation breaks down, and the retrieved values will be biased. EW residual displacement maps (correlation minus synthetic) are shown in Figure 4. The large residual close to the synthetic discontinuity reflects the inability of the correlation window to reliably capture the displacement when the window crosses the discontinuity. Table 3 gives the mean, the standard deviation (std), and the maximum error of the 3 residual maps. PCC has high mean and std error for the EW and NS components, while CNN-DATe is closer to the state-of-the-art COSI-Corr. The latter contains the best mean and std results, yet with some outliers (larger maximal errors).

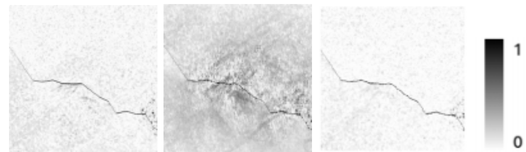


Fig. 4: EW difference maps between the synthetic displacement map and respectively CNN-DATe (left), PCC (center), and COSI-Corr (right)

	Mean		Std		Max	
	WE	NS	WE	NS	WE	NS
CNN-DATe	0.058	0.057	0.060	0.050	1.4	1.4
PCC	0.18	0.13	0.14	0.13	8.9	8.6
COSI-Corr	0.037	0.052	0.058	0.064	2.6	11.

Table 3: Errors statistics (mean, standard deviation and maximum) of our CNN-DATe, PCC and COSI-Corr correlators.

4. DISCUSSION AND CONCLUSIONS

This paper presents a technique to perform estimation of ground deformation using satellite images (medium-resolution Landsat-8), based on CNN. We evaluate 3 models, and the one with the most accurate results (CNN-DATe) was selected, with a precision below 0.1 pixel. The main purpose of the study was to demonstrate, with an evaluation on realistic synthetic displacement maps, the feasibility of a machine learning approach for accurate sub-pixel measurement in the context of surface deformation estimation from remotely sensed satellite imagery. We showed that we already have competitive results with respect to a state-of-the-art method.

Nevertheless, various issues remain to be explored to improve the results. One significant limitation is the calculation of the sub-pixel shifted image when creating synthetic data: sub-pixel re-sampling can introduce bias in the training data which will ultimately limit the achievable precision. To some extent, this bias can be learned, which likely explains why we achieve higher accuracy than traditional phase correlation methods (which do not learn). In future research, we could add non-uniform shifts when training, to be more robust to real displacements. The architecture of our model could also be improved in order to operate with different sizes of windows, or even to output a full displacement field instead of a 2D local vector (e.g. using U-net architectures [13]). Finally, the advantage of a data-driven approach is that additional data could be added for training, giving the model more information to learn the subtle relationships which contribute to the perceived noise in the final correlation maps (e.g. adding illumination conditions associated with an image may allow the illumination bias to be learned). Future developments of data-driven sub-pixel registration techniques based on this encouraging preliminary study should improve the current accuracy, precision, and spatial detail of ground displacement maps.

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