

# sensetrack: a python toolkit for remote-sensing imagery offset-tracking and preprocessing

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## Software

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## Summary

sensetrack is an open-source Python library designed to perform offset-tracking on geo-referenced imagery, with a specific focus on the detection and monitoring of surface displacements induced by landslide processes.

The library offers tools to preprocess and convert data from several satellite missions, including Sentinel-1, COSMO-SkyMed, and PRISMA, into geo-coded GeoTIFFs suitable for displacement analysis.

It provides an integrated and reproducible pipeline for image pair management, offset estimation using different algorithms (including phase correlation and optical flow), and output visualization or export.

sensetrack supports batch processing, modular workflows, and customization through XML-based processing graphs.

## Statement of need

Landslides and mass movement processes pose a significant threat to infrastructure, settlements, and natural landscapes (Eisbacher, 1984; Froude & Petley, 2018; Klose, 2015; Mansour, 2011; Winter et al., 2016). Monitoring ground deformation in active or potentially unstable slopes is critical for risk mitigation and early warning.

While InSAR techniques have proven effective, offset-tracking provides complementary capabilities for detecting large, nonlinear, or fast-moving deformations that challenge conventional phase-based methods (Liu et al., 2025).

There is currently a lack of user-friendly, modular, and extensible Python libraries to support offset-tracking from various satellite platforms. sensetrack addresses this need by integrating image preprocessing, standardized conversion to geo-referenced formats, and multiple offset-tracking algorithms into a coherent workflow.

Unlike many existing tools for SAR-based displacement tracking that rely on Google Earth Engine (GEE), sensetrack runs entirely in a local Python environment. This design choice ensures full reproducibility, data privacy, and ease of integration in institutional or offline workflows.

## State of the field

SenseTrack and DICpy are Python libraries for displacement estimation from image data that address different application domains. SenseTrack targets remote sensing and offset-tracking of remote sensing imagery (SAR and optical), integrating SNAP/GPT preprocessing and

georeferenced workflows, and relying on dense optical-flow and phase-correlation algorithms implemented in OpenCV to process large scenes and produce GIS-ready displacement products. In contrast, DICpy is designed for Digital Image Correlation in laboratory and engineering experiments, focusing on subset- or global-based correlation methods to achieve high sub-pixel accuracy in displacement and strain measurements on high-resolution speckle images.

## Software design

The processing pipeline was conceived as a combination of independent tasks. In this framework, SenseTrack's design emphasizes a modular architecture: subpackages (`ot`, `snap_gpt`, `sentinel`, `cosmo`, `prisma`) expose interfaces for inputs, outputs, and algorithms, so individual components can be swapped or extended without changing the overall processing chain. Preprocessing routines, algorithm wrappers, and image-processing dispatchers are decoupled from orchestration logic to maximize reuse, testability, and maintainability. The project deliberately avoids dependencies with proprietary platforms and instead relies on open, standardized tools such as SNAP-GPT, rasterio, h5py, and geopandas, enabling local execution, full data control, reproducible pipelines, and easier deployment in diverse research and operational environments.

## Research impact statement

Offset-tracking methods based on image intensity, such as optical flow and windowed cross-correlation, provide a complementary approach to phase-based InSAR techniques. While InSAR enables highly precise deformation measurements under conditions of phase coherence, offset tracking is less sensitive to decorrelation and can capture larger displacements, making it suitable for rapidly moving or heterogeneous terrains. As a result, these methods are particularly effective for large-area screening and monitoring of landslide activity, where they can identify spatial patterns and kinematic trends at regional scale. When integrated with InSAR analyses, offset-tracking approaches contribute to accelerating the development of comprehensive knowledge frameworks that support hazard assessment and inform land-use and territorial planning.

## Functionality and features

### Offset-tracking module

The `sensetrack.ot` subpackage provides core functionalities for optical flow analysis, image normalization, interface management, and CLI for offset tracking. It is designed to work with satellite images and raster data, offering advanced algorithms and support tools for research and operational applications.

The `ot.interfaces.py` sub-module provides the foundational classes and utilities for managing images and implementing optical tracking algorithms within the project. At its core is the `Image` class, which encapsulates multi-band image data along with essential metadata such as georeferencing information, nodata handling, and band management. This class supports a variety of operations, including splitting images into individual bands, checking for coregistration between images, and accessing band-specific data, all while maintaining a consistent interface for both single-band and multi-band images. The design ensures that images are handled robustly, with automatic inference and management of nodata values and support for affine transformations and coordinate reference systems.

Complementing the image management functionality is the `OTAlgorithm` abstract base class, which serves as the blueprint for all offset tracking algorithms in the toolkit, implemented in `ot.algorithms.py` sub-module. It provides mechanisms for serializing and deserializing

84 algorithm parameters from dictionaries, JSON, or YAML files, facilitating reproducibility and  
85 easy configuration. Additionally, it includes utility methods for converting pixel offsets into  
86 physical displacements, ensuring that results are meaningful in both pixel and real-world  
87 coordinates.

## 88 Implemented algorithms

### 89 1. OpenCVOpticalFlow

90 The `algorithms.OpenCVOpticalFlow` algorithm provides a Python interface to the  
91 Farneback dense optical flow method (Horn & Schunck, 1981), as implemented in  
92 OpenCV's `calcOpticalFlowFarneback` function (Farneback, 2003). This approach  
93 estimates the motion field between two images by analyzing the apparent movement  
94 of pixel intensities, producing a dense displacement vector for every pixel. The core of  
95 the algorithm relies on constructing image pyramids, which allow it to capture both  
96 large and small displacements by progressively analyzing the images at multiple scales.  
97 At each level, the algorithm models local neighborhoods with polynomial expansions,  
98 enabling it to robustly estimate motion even in the presence of noise or textureless  
99 regions. The flexibility of the implementation allows users to fine-tune parameters such  
100 as the pyramid scale, window size, number of iterations, and the degree of smoothing,  
101 thus balancing accuracy and computational efficiency. After computing the flow, the  
102 results are transformed into images representing the horizontal and vertical components  
103 of the displacement, as well as the overall magnitude

### 104 2. SkiOpticalFlowILK

105 The `algorithms.SkiOpticalFlowILK` (Lucas & Kanade, 1997) algorithm offers a Python  
106 interface to the Inverse Lucas-Kanade (ILK) method for dense optical flow estimation, as  
107 implemented in `scikit-image`'s `optical_flow_ilk` function. This approach is designed to  
108 estimate the pixel-wise motion between two images by analyzing local intensity variations  
109 and tracking how small neighborhoods shift from the reference to the target image. The  
110 ILK method operates by minimizing the difference between the reference and the warped  
111 target image, iteratively refining the displacement field to achieve the best alignment. It  
112 is particularly well-suited for scenarios where the motion is relatively small and smooth,  
113 as it assumes that the displacement within each local window can be approximated  
114 linearly. The algorithm allows for customization of parameters such as the radius of the  
115 local window, the number of warping iterations, and the use of Gaussian smoothing  
116 or prefiltering, enabling users to adapt the method to different noise levels and image  
117 characteristics. After computing the displacement vectors, the results are transformed  
118 according to the affine properties of the target image, producing output images that  
119 represent the horizontal and vertical components of the motion, as well as the overall  
120 displacement magnitude

### 121 3. SkiOpticalFlowTVL1

122 The `algorithms.SkiOpticalFlowTVL1` (Zach et al., 2007) algorithm provides a  
123 Python interface to the TV-L1 optical flow method, as implemented in `scikit-image`'s  
124 `optical_flow_tv1` function. This approach is based on a variational framework  
125 that seeks to estimate the dense motion field between two images by minimizing an  
126 energy functional composed of a data attachment term and a regularization term. The  
127 TV-L1 method is particularly robust to noise and outliers, thanks to its use of the  
128 L1 norm for the data term and total variation (TV) regularization, which encourages  
129 piecewise-smooth motion fields while preserving sharp motion boundaries. The algorithm  
130 iteratively refines the displacement field through a multi-scale, coarse-to-fine strategy,  
131 allowing it to capture both large and small motions. Users can adjust parameters  
132 such as the strength of the data and regularization terms, the number of warping and  
133 optimization iterations, and the use of prefiltering, making the method adaptable to  
134 a wide range of imaging conditions. After the optical flow is computed, the results  
135 are mapped to the affine space of the target image, producing output images for the  
136 horizontal and vertical components of the displacement, as well as the overall magnitude

#### 4. SkiPCC\_Vector

The `algorithms.SkiPCC_Vector` algorithm implements a phase cross-correlation (PCC) approach (Foroosh et al., 2002) for estimating local displacements between two images, leveraging the `phase_cross_correlation` function from `scikit-image`. Unlike traditional optical flow methods that rely on intensity gradients, this technique operates in the frequency domain. Since the base function `phase_cross_correlation` outputs a single displacement for two input arrays, this implementation provides an utility for splitting the two images into several sub-arrays in a rolling-window fashion (see the `stepped_rolling_window` help for further details), than `phase_cross_correlation` is performed for each pair of windows, and the results are collected in a dataframe-like structure where each record is associated with displacements in the two directions (fields `RSHIFT` and `CSHIFT` for row and column displacement respectively), the resultant displacement (`L2`), and the normalized root mean square deviation between analyzed moving windows (`NRMS`). By using phase normalization, the method enhances its sensitivity to translational differences while suppressing the influence of amplitude variations. The process can be further refined by adjusting the window size, step size, and upsampling factor, allowing for subpixel accuracy in the displacement estimates.

### Command-line interface (CLI)

Each of the aforementioned algorithms can be executed through the command line. The CLI interface in this project serves as a flexible bridge between users and the core image processing algorithms, enabling command-line execution and configuration of complex workflows. At its foundation, the CLI is built around a generic base class that handles argument parsing, input validation, and algorithm instantiation. Each algorithm-specific module, such as those for OpenCV optical flow, phase cross-correlation, or `scikit-image` methods, extends this base class to introduce tailored command-line options reflecting the parameters and features of the underlying algorithm. Users interact with these modules by specifying arguments directly in the terminal, which are then parsed and mapped to the corresponding algorithm's configuration. The general workflow involves:

1. Parse command-line arguments
2. Load reference and target images
3. Coregistration
4. Preprocessing
5. Run the selected offset-tracking algorithm
6. Export the displacement results to the specified output file

This design streamlines batch processing and reproducible analysis, allowing users to switch between different algorithms or parameter sets with minimal effort. The CLI modules that depend on `cli.py` inherit its structure, ensuring consistent behavior and a unified user experience across the toolkit.

### Additional modules

The `snap_gpt` module is designed to facilitate the interaction with the SNAP Graph Processing Tool, a widely used platform for satellite image analysis. By providing programmatic access to SNAP's capabilities, this module enables users to automate complex processing chains, manage graph-based workflows, and integrate SNAP's advanced algorithms into custom remote sensing pipelines. Its architecture supports the orchestration of preprocessing, calibration, and product generation tasks, making it a valuable asset for large-scale and reproducible satellite data analysis.

The `sentinel` module is specialized for handling data from the Sentinel satellite missions, which are part of the Copernicus program. It offers a comprehensive set of tools for reading, preprocessing, and analyzing Sentinel imagery, with routines tailored to the unique formats and metadata structures of these datasets. The module streamlines common operations such

as radiometric correction, geometric alignment, and feature extraction, ensuring that users can efficiently prepare Sentinel data for further scientific or operational use.

The prisma module focuses on the PRISMA hyperspectral satellite, providing dedicated functions for extracting and manipulating its spectral information. It supports the retrieval of hyperspectral cubes, metadata parsing, and the transformation of raw data into analysis-ready products.

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## AI usage disclosure

Generative AI models were used to assist with bug fixing and editing selected portions of the manuscript. The design, implementation, and testing of the software modules were performed entirely by the authors.

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