On the effective use of GeFolki

GeFolki:
the swiss army knife
for co-registration of remote sensing images

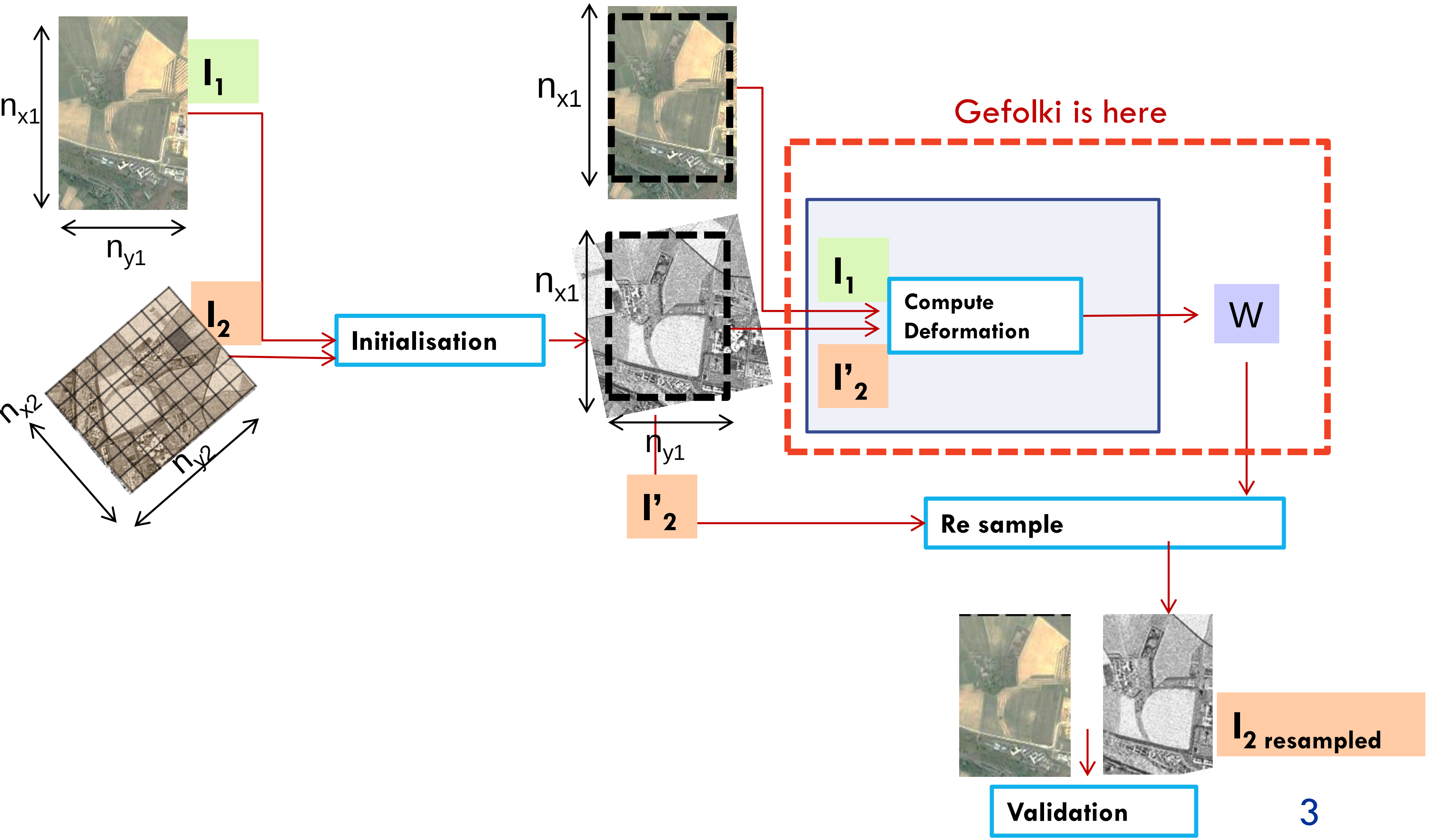
ONERA

THE FRENCH AEROSPACE LAB

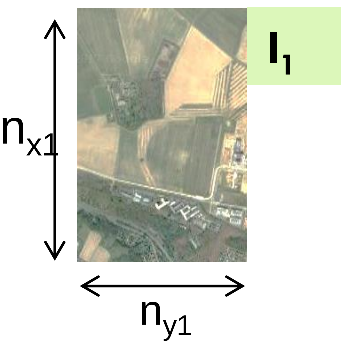
Content

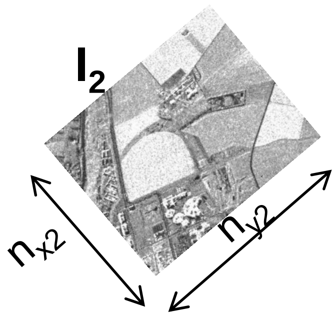
- What are the main steps of co-registration?
- How does GeFolki work?
  and how it is positionned among other tools?
- Examples of practical cases
- Practical exercises

A general scenario

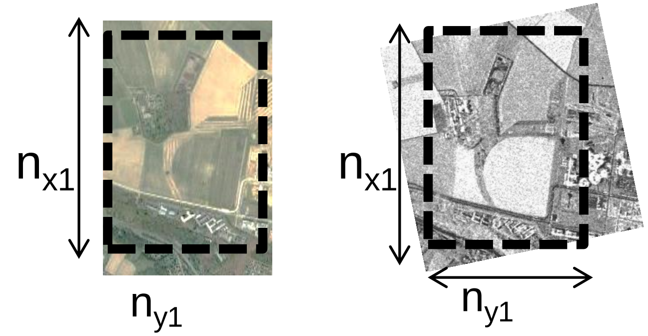


The step of initialisation





Example:
Master: geocoded optical data

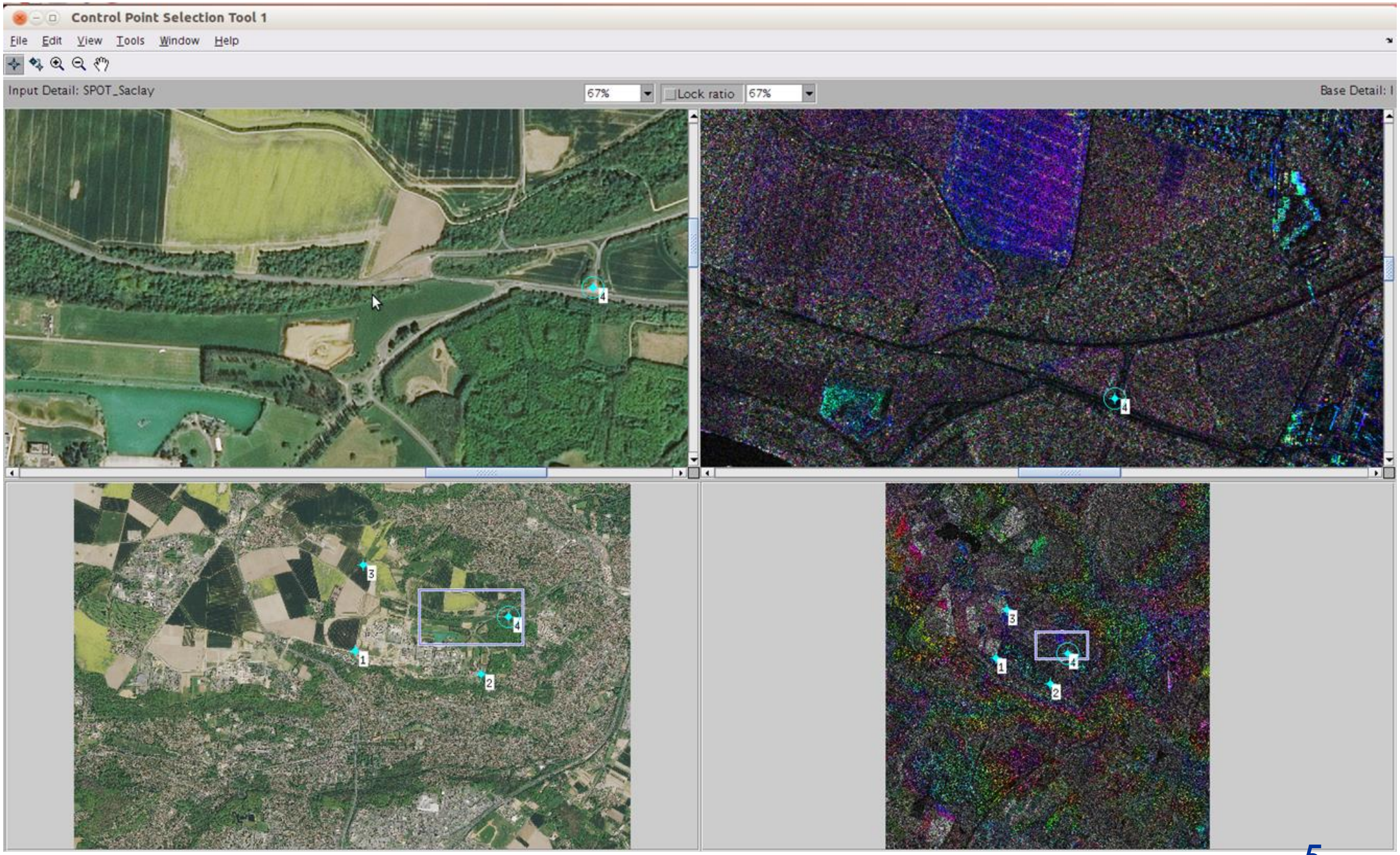


Diffculty to estimate flow

Quality of initialisation

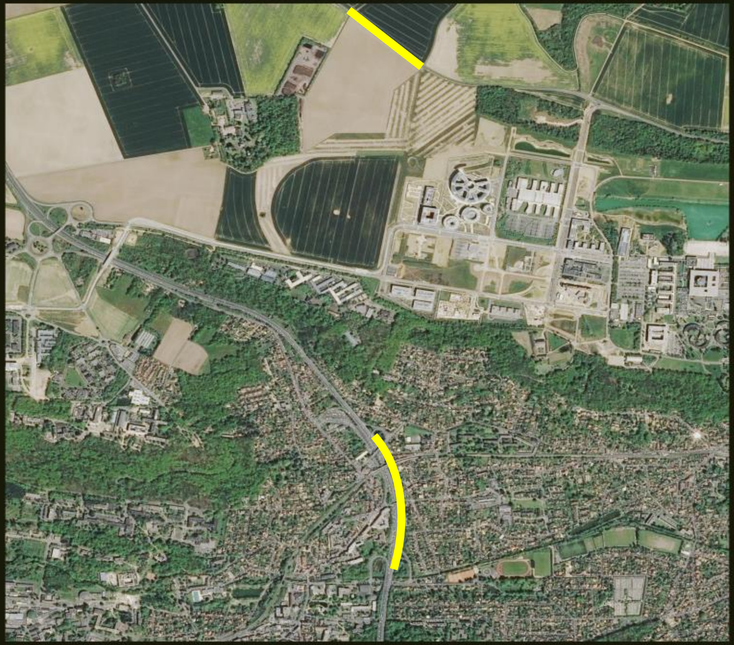
Input Slave Image	GRD SAR image	Image radar SLC	Image radar SLC	Image radar SLC
Initialisation	Ré-échantillonnage sur taille pixel optique	Géoréférencement	Prise de points d'amer	Transformation simple des axes (azimut,range) en (X,Y)
Requises	Partir d'un produit _Ground	Données auxiliaires : DEM, trajectoires + Logiciels/algorithmes	Opérateur	Connaissance minimale du cap et de l'incidence

Example of intialisation with Control Points



Example using different initialisations

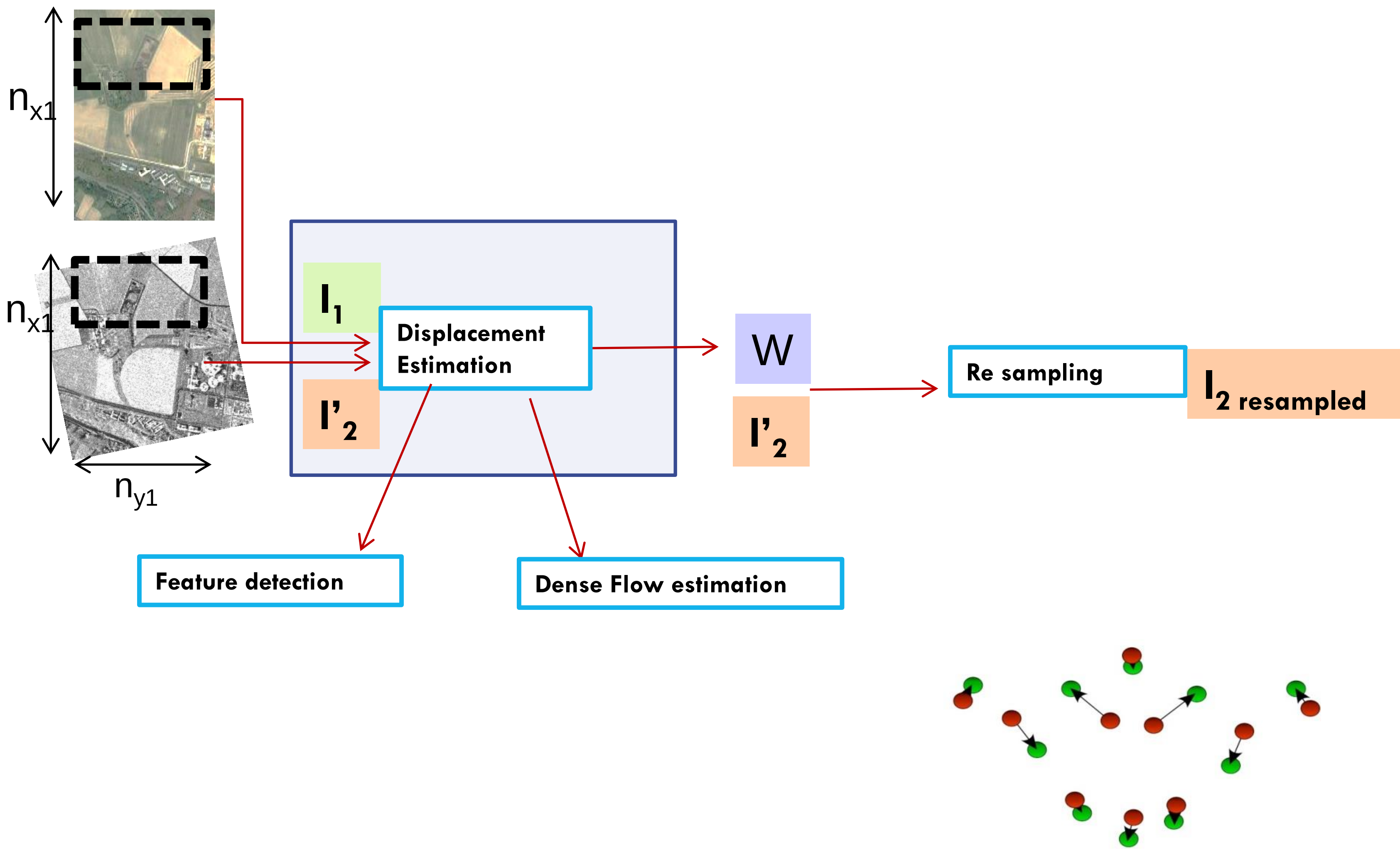
- Image TerraSAR-X 1m over SPOT 1,5m
- Initialisation using control points and projective transformation



Validation : qualitative representations

Colored composition	Mosaic	Animation
		

Flow estimation



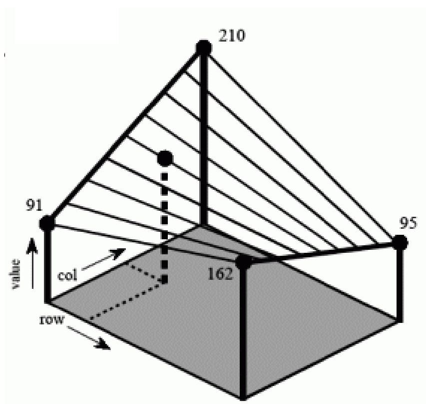
Resampling

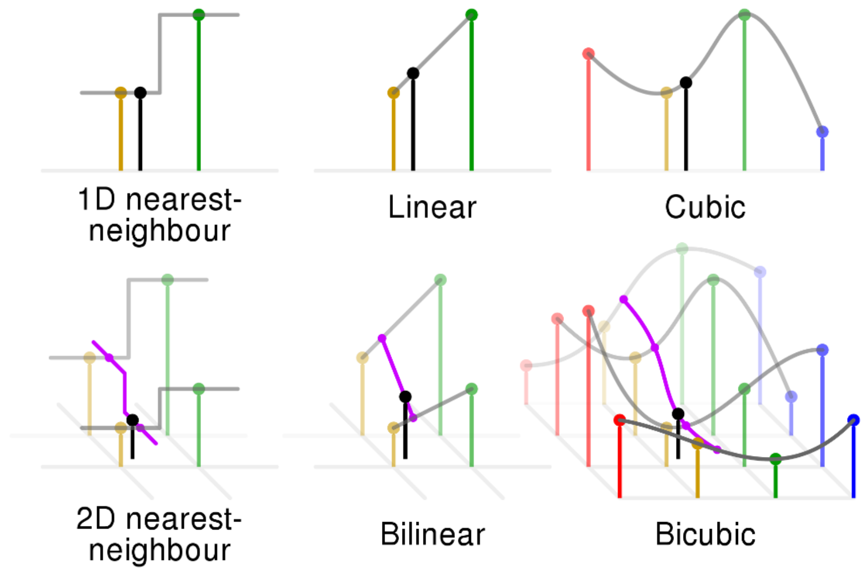
W

I'_2 → **Re sampling** → **I_2 resampled**

Closest Neighbours

Bilinear,…





Wikipedia Commons, Cmglee

Particular case: SAR images

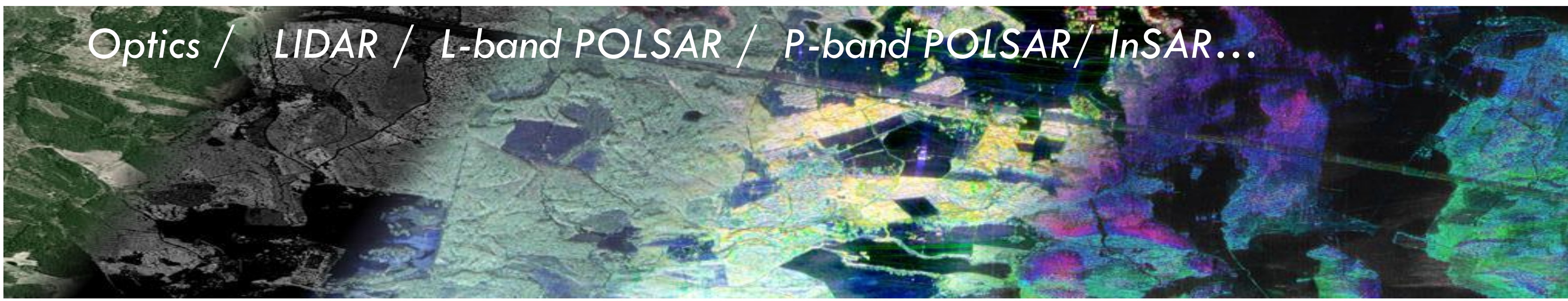
Before re-sampling: center spectra, zero-padding

Why GeFolki ?

- Remote sensing: more and more images, with various sensors
- Precision Need for high resolution, Fast results using time-series/big data

The approach of GeFolki

- Based on historic of Onera



Folki — **F.Champagnat, G. Le Besnerais (2005)**

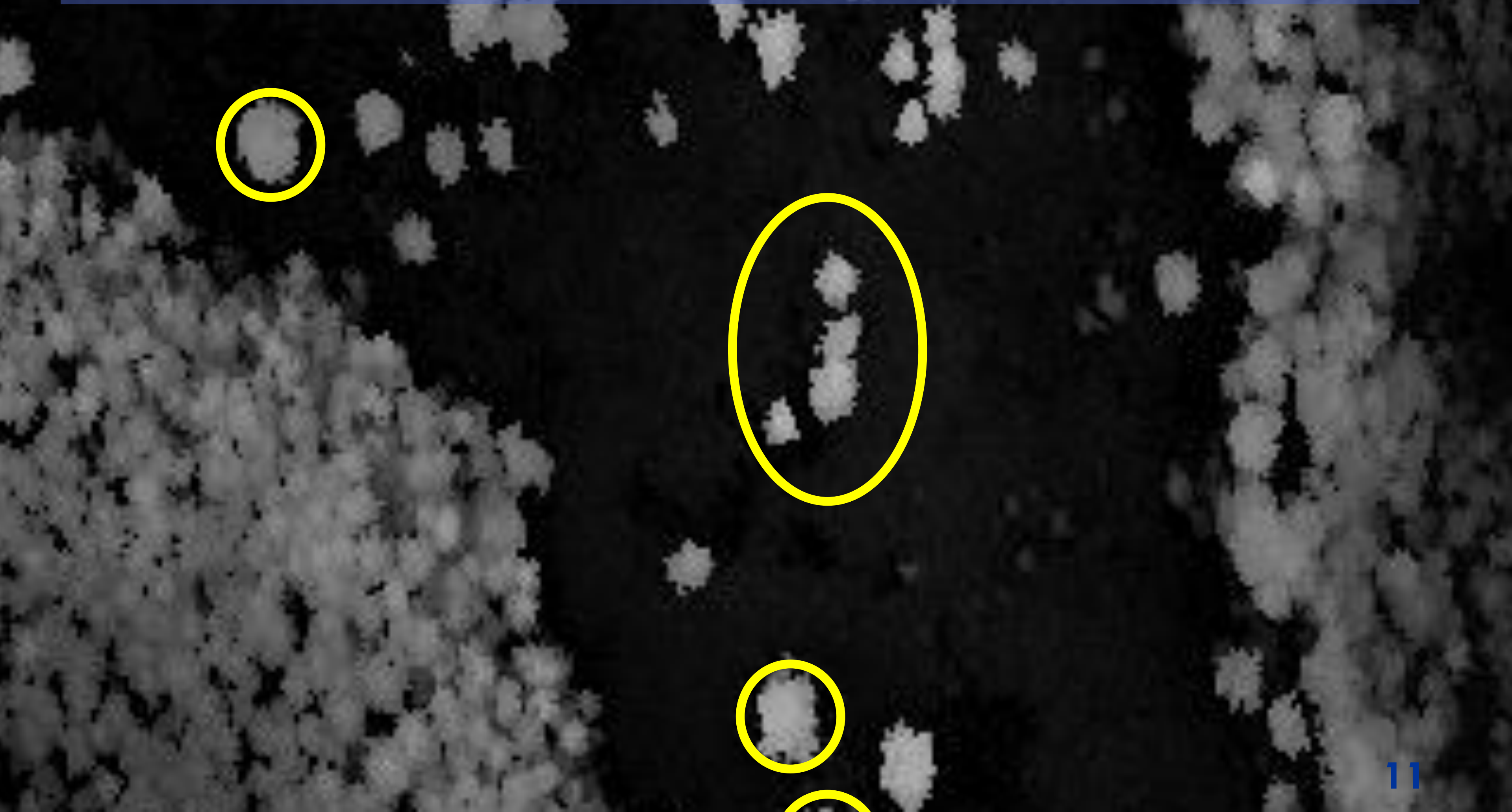
eFolki — **A. Plyer (2013)**

GeFolki — **SAR(2014)**

Optique/radar (2015)

Example: LIDAR / RADAR by georeferencing

« God is in the detail »



Outline

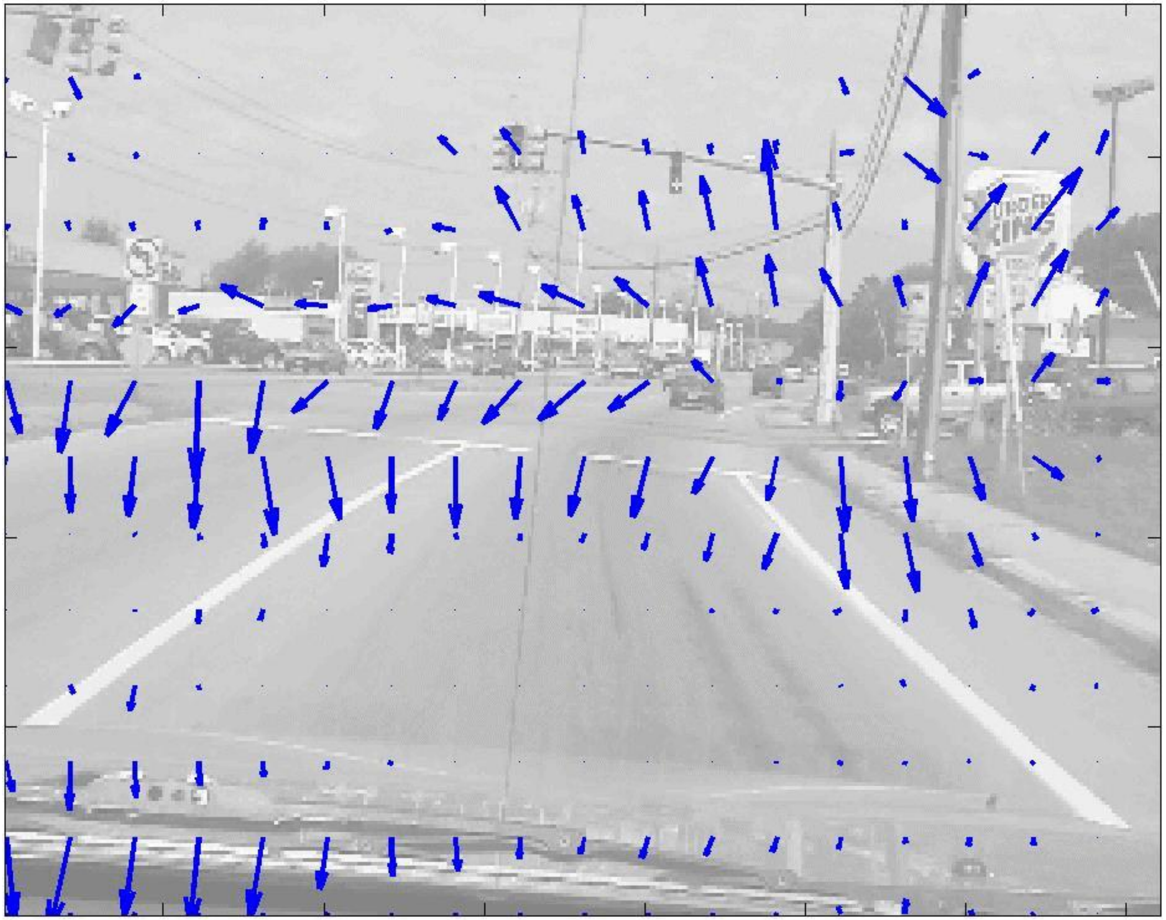
- What is a optical flow method ?
  What is GeFolki?

- Why and when you need GeFolki for remote sensing images ?

- Results

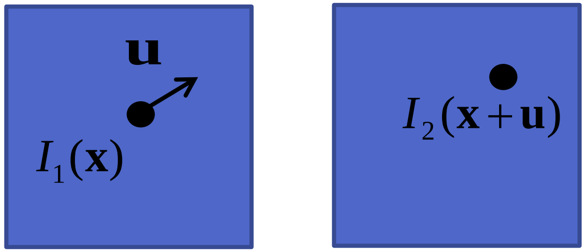
What is a flow estimation method?

The flow $\mathbf{u}(\mathbf{x})$ is the displacement between two frames



One frame

Another frame



Result : optical flow image

Estimation of the displacement vector **for each pixel**

The optical flow methods

Key assumption

$I_1(\mathbf{x}) \approx I_2(\mathbf{x+u})$

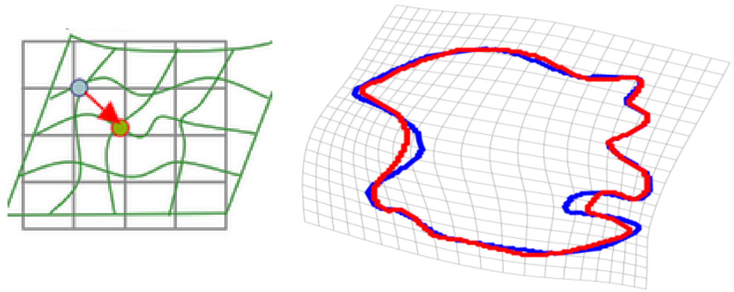
Brightness constancy: a point in I_1 looks the same in I_2

Small motion: points do not move very far

$I_2(\mathbf{x+u}) = I_2(\mathbf{x}) + \nabla \mathbf{I} .u$

Optical flow equation

$I_2(\mathbf{x}) - I_1(\mathbf{x}) + \nabla \mathbf{I} .u = 0$



Ill conditioned

- Local methods
  Lucas-Kanade…

Assumes the flow is locally constant

- Global methods
  Horn and Schunk

introduces a global constraint of smoothness

GeFolki method: among Lucas-Kanade algorithms

Criterion $\mathrm{J}(\mathbf{u}\,;\mathbf{x}) = \sum_{\mathbf{x}'\in S} \omega(\mathbf{x}'-\mathbf{x})\big(I_1(\mathbf{x}') - I_2(\mathbf{x}'+\mathbf{u}(\mathbf{x}))\big)^2$

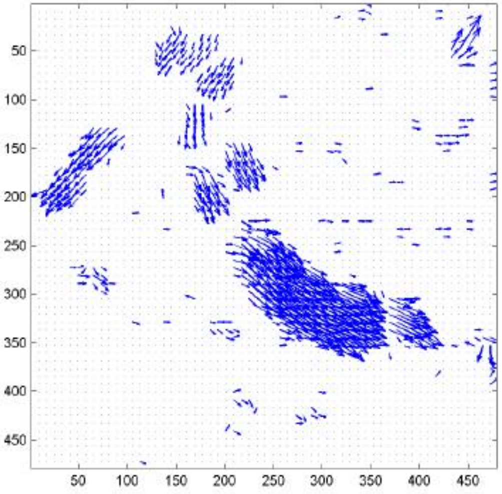
eFolki (2013, A. Plyer)

Parallel Computation for GPU

replace I_1 and I_2 by $f_1(I_1)$ and $f_2(I_2)$

Express the gradient…

- Application: video, 3D navigation, etc.



In the case of remote sensing images

<u>Key assumption</u>

$I_1(\mathbf{x}) \approx I_2(\mathbf{x+u})$

Brightness constancy: a point in I_1 looks the same in I_2

Small motion: points do not move very far

$I_2(\mathbf{x+u}) = I_2(\mathbf{x}) + \nabla \mathbf{I} \,.\mathrm{u}$

Optical flow equation

$I_2(\mathbf{x}) - I_1(\mathbf{x}) + \nabla \mathbf{I} \,.\mathrm{u} = 0$

Example SAR/LIDAR images

~~small motion~~

~~brightness constancy~~

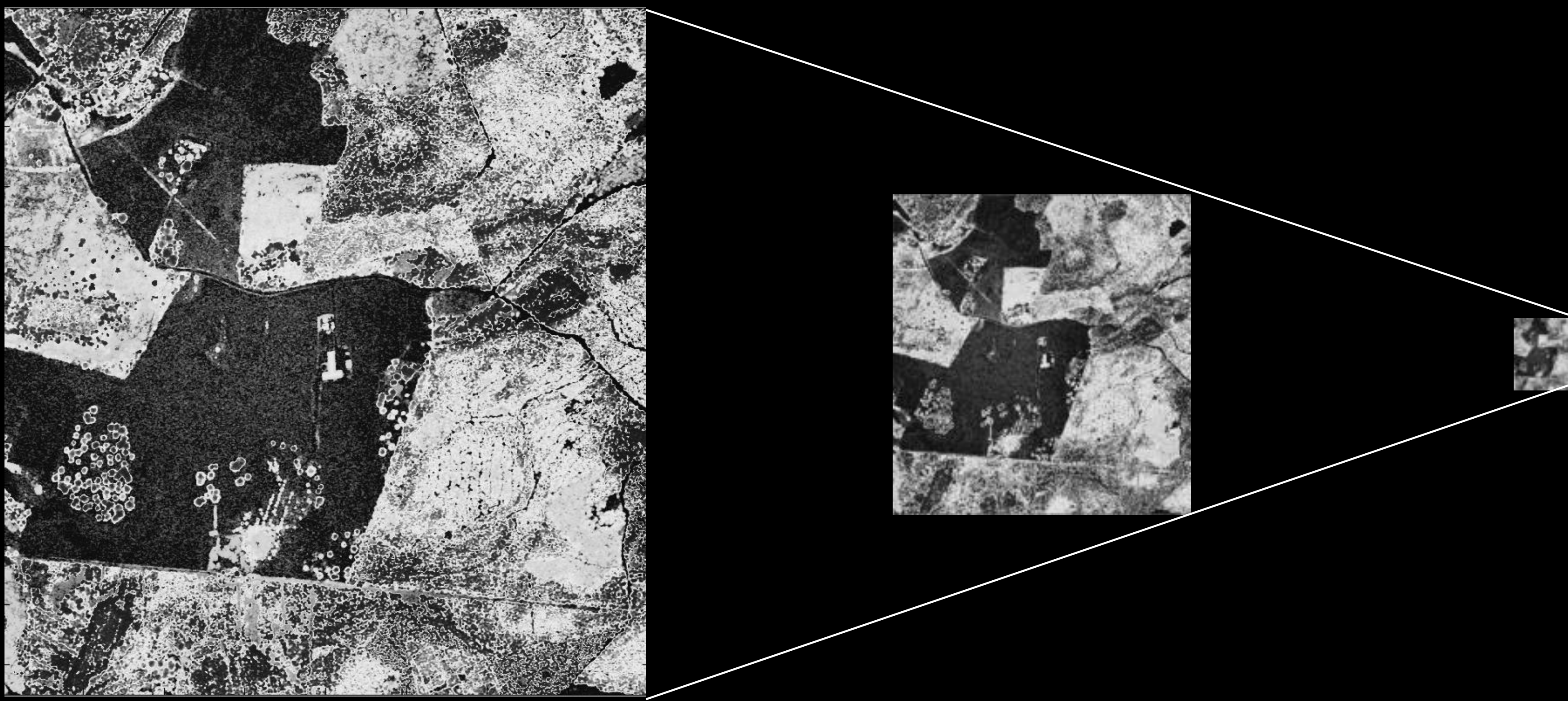
In the case of remote sensing images

Example SAR/LIDAR images

~~small motion~~

~~brightness constancy~~

In the case of remote sensing images



Example SAR/LIDAR images

small motion

~~brightness constancy~~

In the case of remote sensing images

Example SAR/LIDAR images

small motion

$\boxed{\text{brightness constancy}}$

$$I_1 \qquad\qquad I_2$$

$$\downarrow \qquad\qquad \downarrow$$

$$f_1(I_1) \approx f_2(I_2)$$

Our solution:

$$\boldsymbol{f_1 = R \circ f} \qquad\qquad \boldsymbol{f_2 = R \circ g \circ f}$$

Rank filtering: The rank of the pixel intensity among neighboords

Edge preserving filtering: **rolled guidance filter**

Contrast Inversion decision

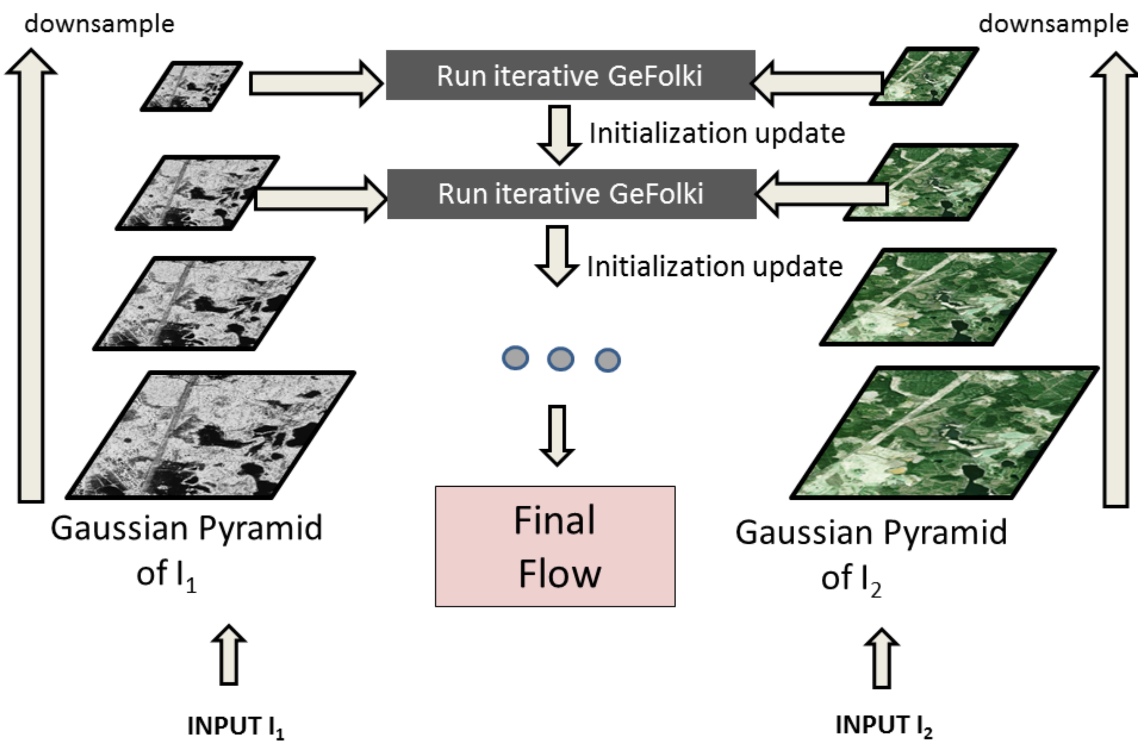
In the case of remote sensing images

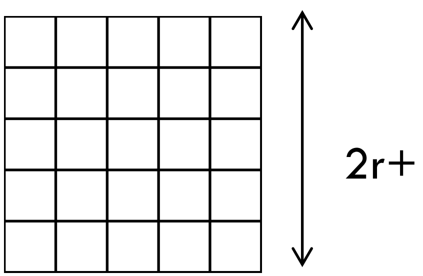
IT ALWAYS SEEMS IMPOSSIBLE UNTIL

IT'S DONE.

Large displacements

- Pyramid representation of the image
- Estimation of the optimization on an iterative-based method





Contrast inversion: the key idea

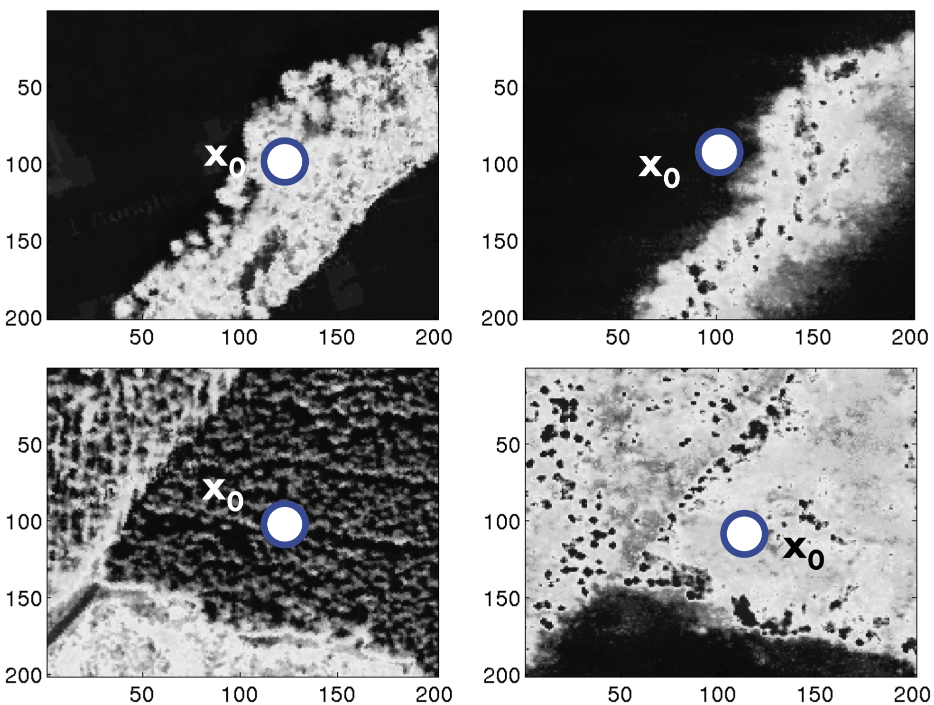
– Inversion criterion

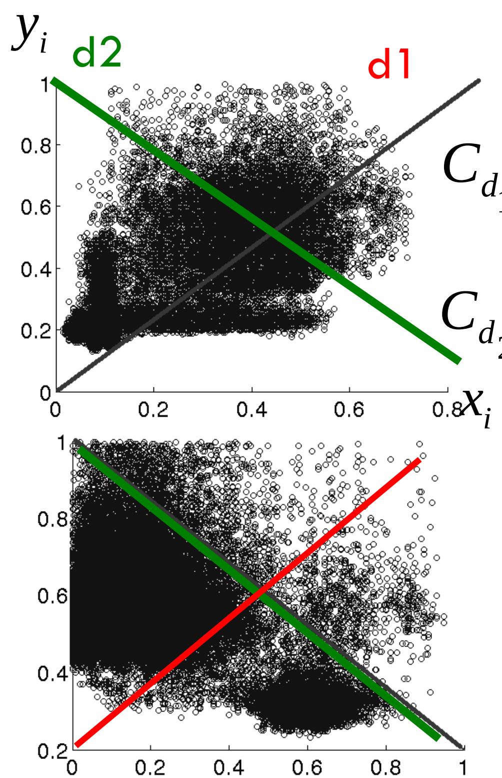
Distance to lines:

(d1) y=x

(d2) y=1-x

Windoc optical *w* | Window radar *w*





$$C_{d_1}(\mathbf{x_0}) = \sum_{i \in w} |x_i - y_i|$$

$$C_{d_2}(\mathbf{x_0}) = \sum_{i \in w} |1 - x_i - y_i|$$

Decision :

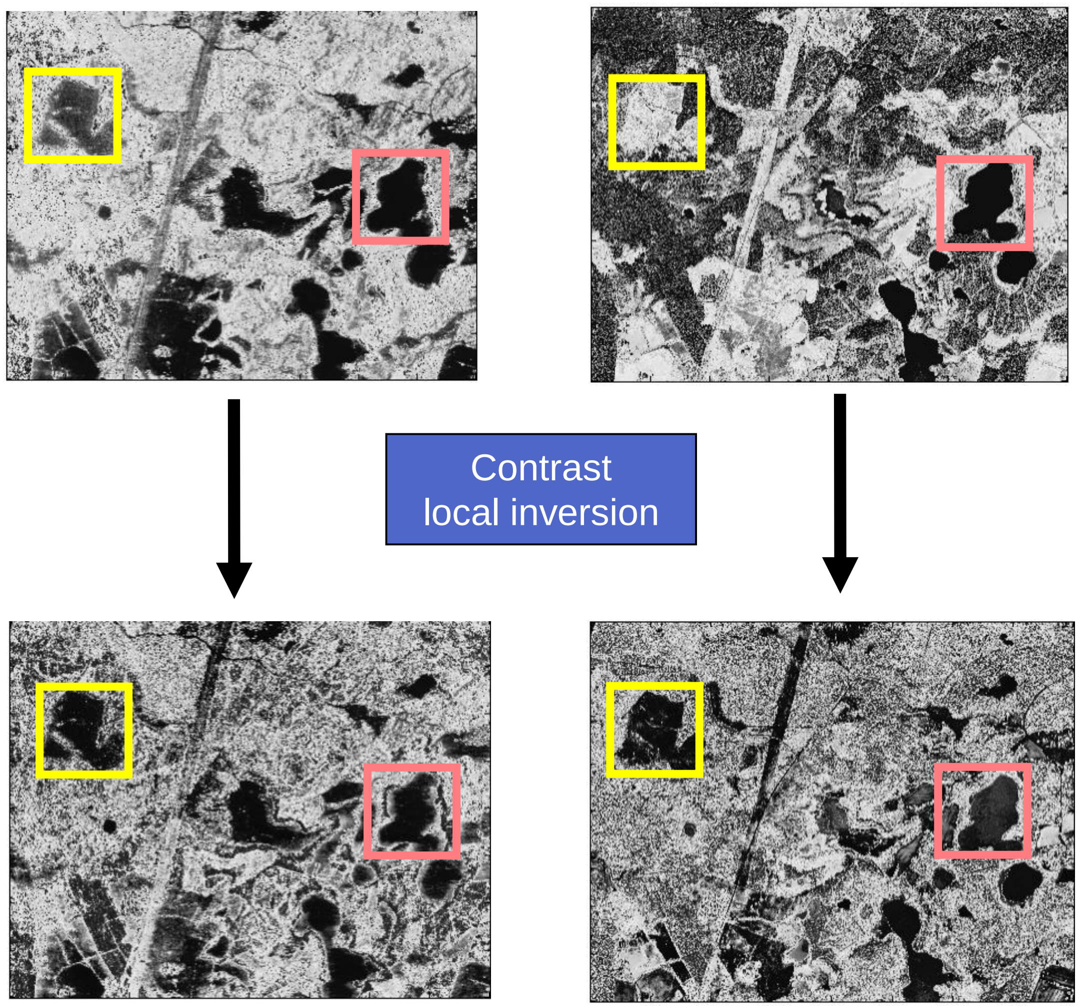
if C_{d1} ($\mathbf{x_0}$) > C_{d2} ($\mathbf{x_0}$)

then I_2 ($\mathbf{x_0}$)

else no inversion

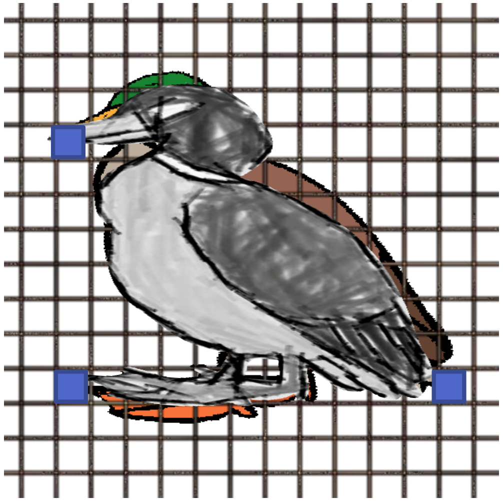
Result for contrast inversion

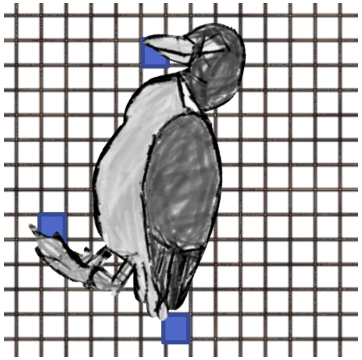
Radar image **Optical image**



Parameters

- Choosing initialisation



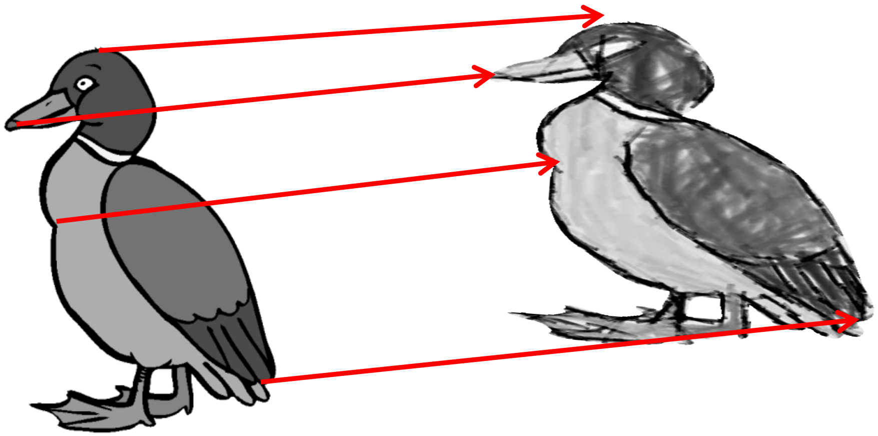


- Choose one band

- Activate or not contrast inversion decision
- R : radius of window
- r: Radius for rank-filtering
- L: number of pyramid levels
- K : number of interations

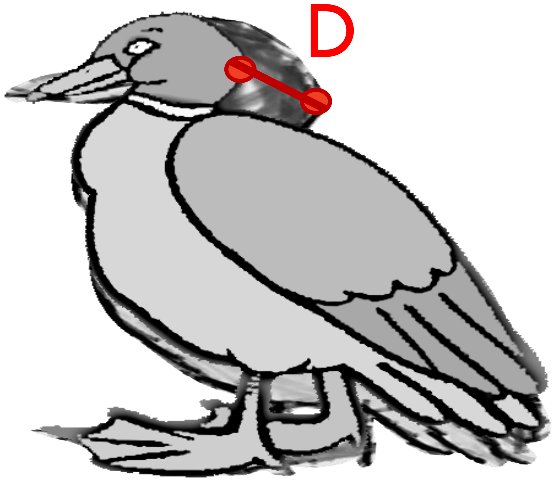
Parameters for GeFolki

Pyramid Levels: Pyramid decomposition to look for large displacements
Radius: size of patchs that must correlate
Iteration numbers: to find the minimum of the function by the minimum gradient method
Rank: Size of the rank filtering.



Objective: for each pixel of the image, establish the translation that allows to find the corresponding pixel in the other image

Pyramid level number L

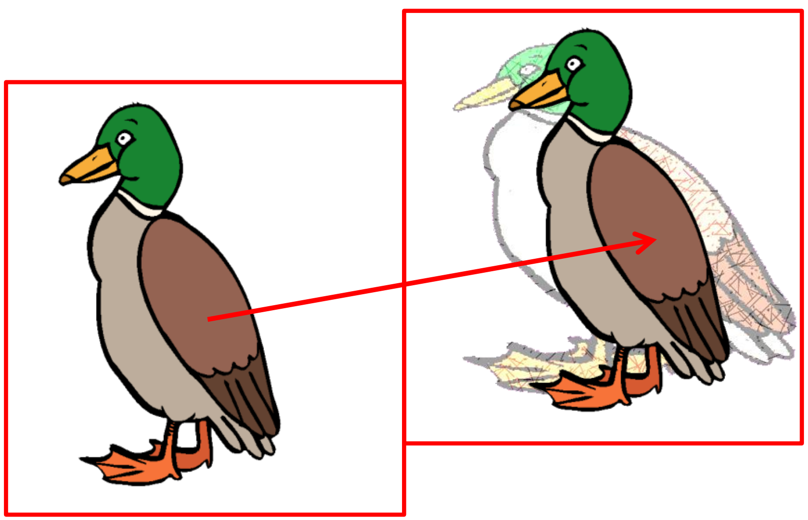


The simplest parameter to fix!
Have a large estimate of displacement to estimate D
Choose the smallest L such that $2^L > D$

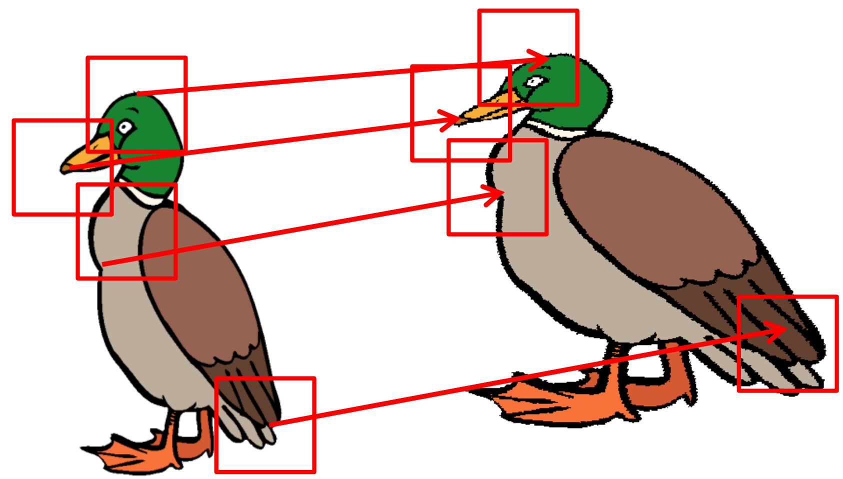
The radius (half-size of patch)

Compromise:

- Large size -> the structuring elements will be "recognized" BUT the flow will estimate a global transformation
- Small size -> will adapt to small-scale deformation (duck's head) but may increase confusion with another element



A large radius is robust to search for a large global translation.
But does not allow to find small deformations



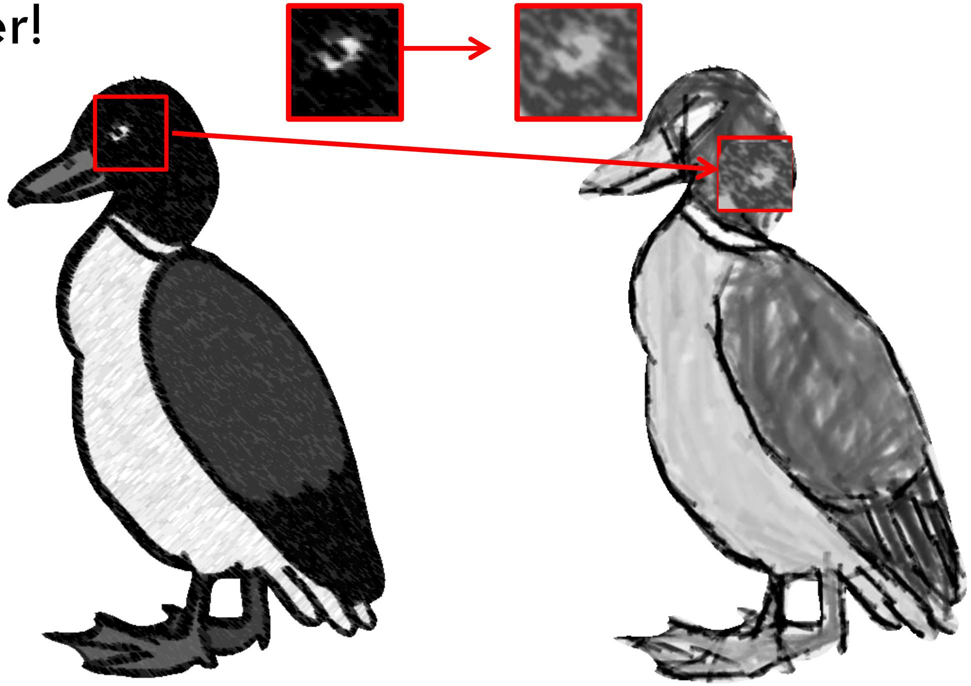
Only a small radius makes it possible to find "local" deformations

Parameters of less importance

- Rank: typically 4.
- Iteration numbers :
  typically 8 to 12 for optical images, smaller for SAR images (2 to 4)

Texture influence, pre-processing

If texture are very different, false matching probability increases. Especially when the radius is small and a high pyramid level number!

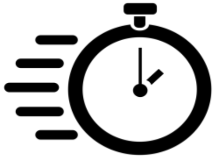


- Try to filter your images (rolling guidance filter, NL-mean, NL-SAR, etc.
- Increase radius, especially for SAR images (speckle)

Why applying GeFolki to remote sensing?

- **Generic**: optical (stereo), radar(interferometry), lidar…
- **Self-sufficient**: does not require auxiliary data
  (no DEM, no orbit tracks)

- **Fast**: adapted to video processing, implemented on GPU



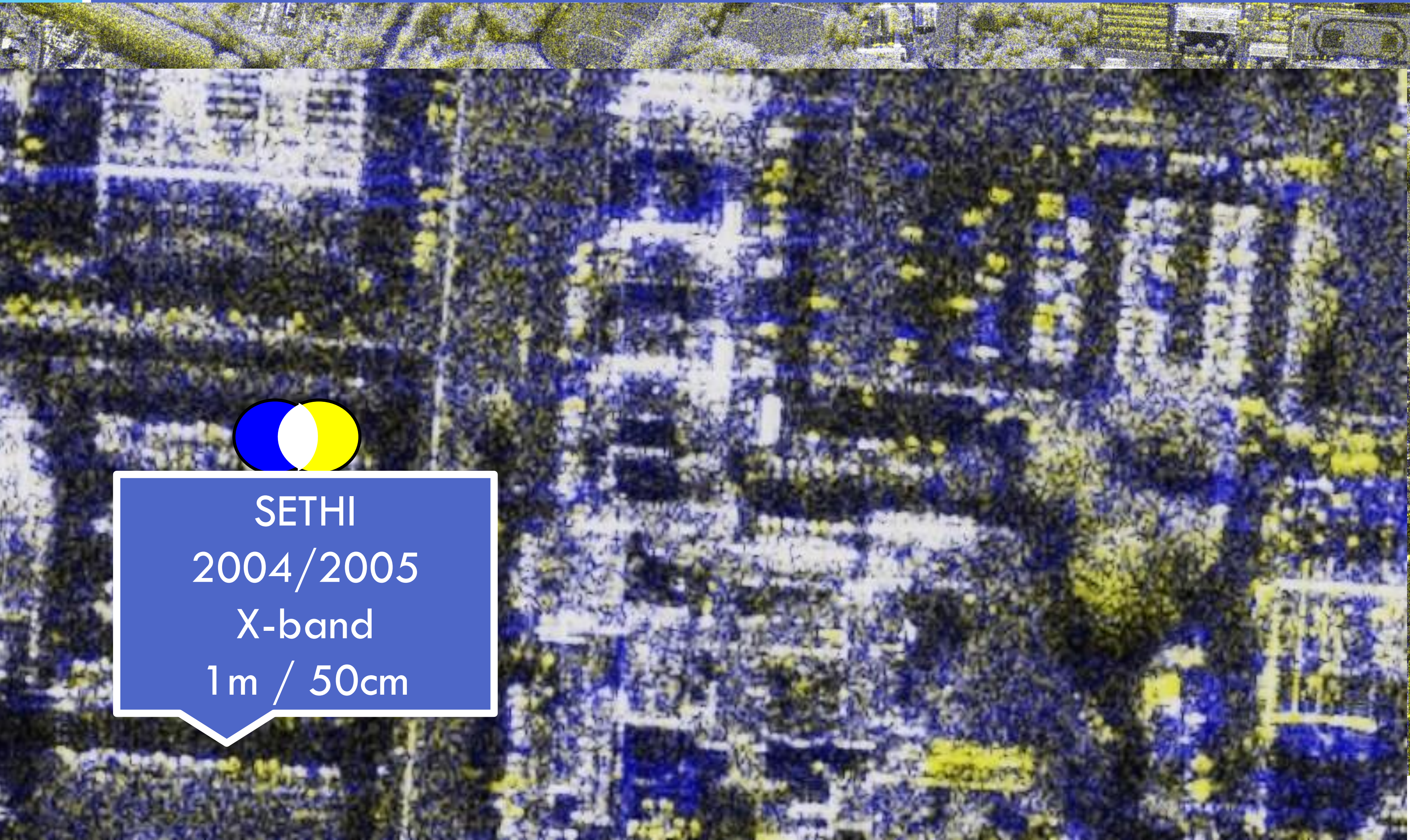
- **Non parametric:** does not require selection of features
- **Dense**: ultra fine grid of deformations adapted to very high resolution

AND PRECISION ?

Interferometry: successful in very challenging contexts

Heterogenous: better than fine geocoding

results on SAR/SAR multiresolution

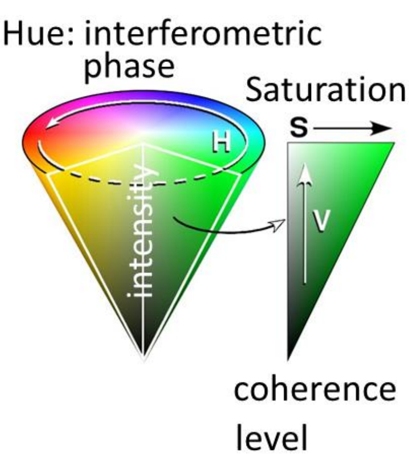


results on SAR interferometry: forest

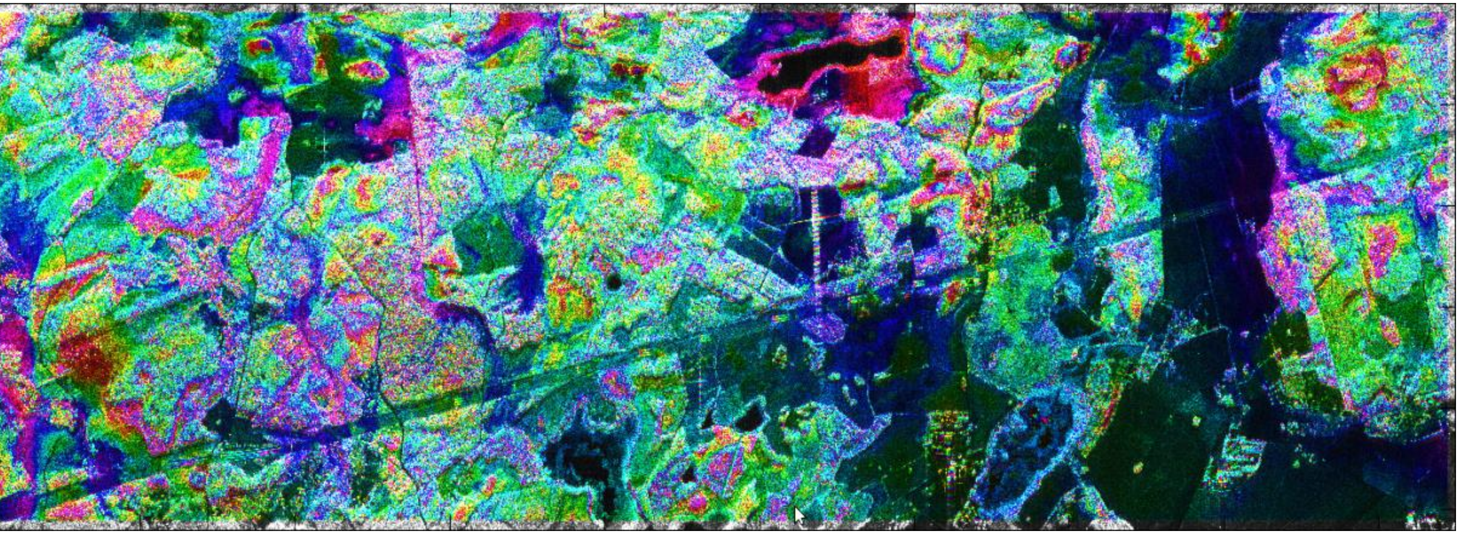
SETHI
2010
P-band
80cm

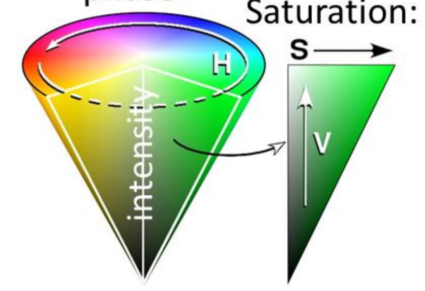
Results obtained:

- ❑ Without orbit tracks
- ❑ Without MNT
- ❑ Without any selection of point



results on SAR interferometry: forest



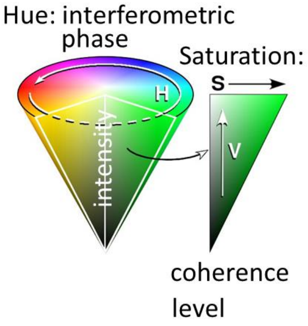


SETHI
2010
L-band
1m

- ❑ Very fast variation of the interferometric phase because of small ambiguity height

results on SAR interferometry : urban

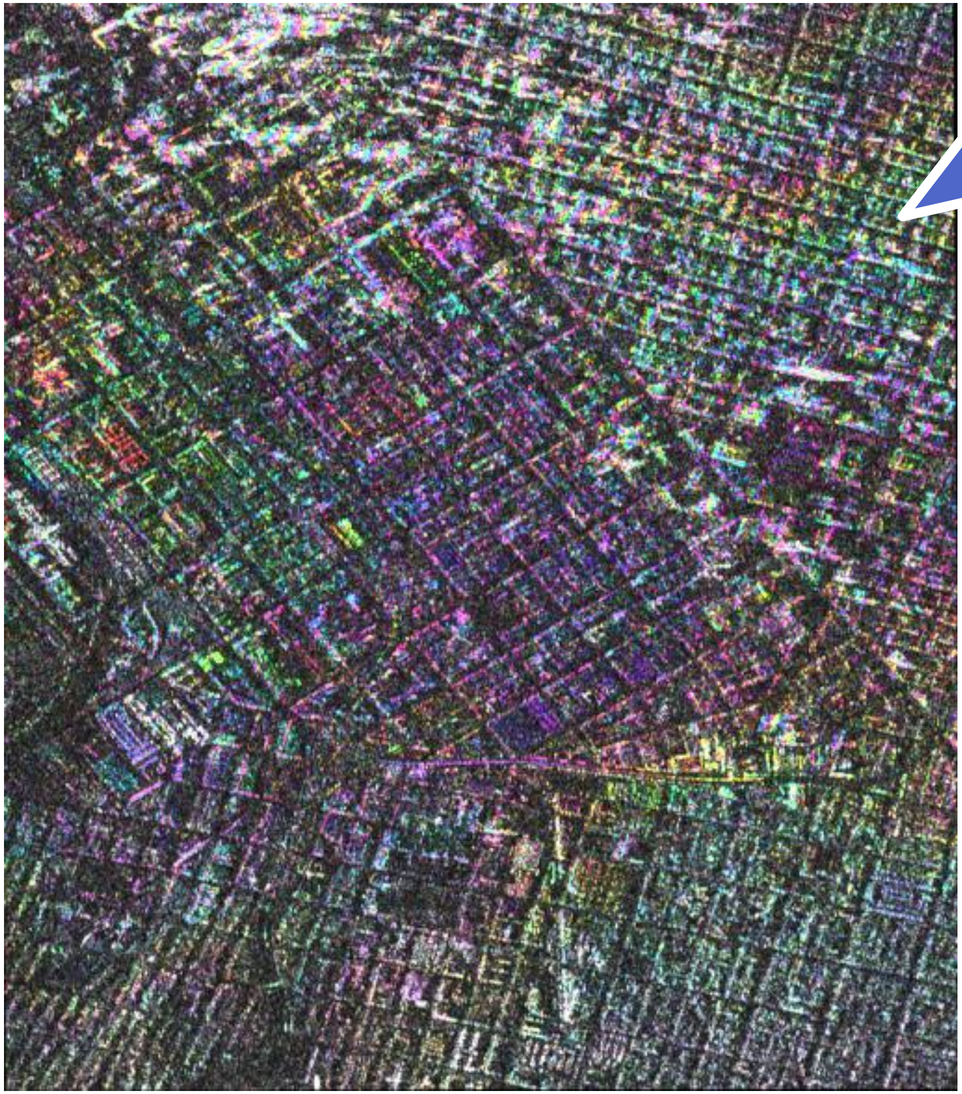
TSX
2011
X-band
1m



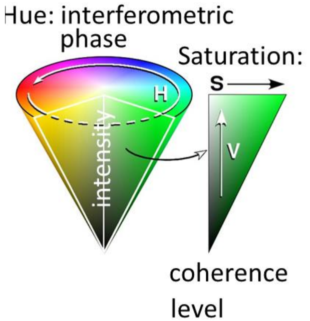
Temporal baseline: 11 days

Results obtained:
- Without orbit tracks
- Without MNT
- Without any selection of point

results on SAR interferometry : urban



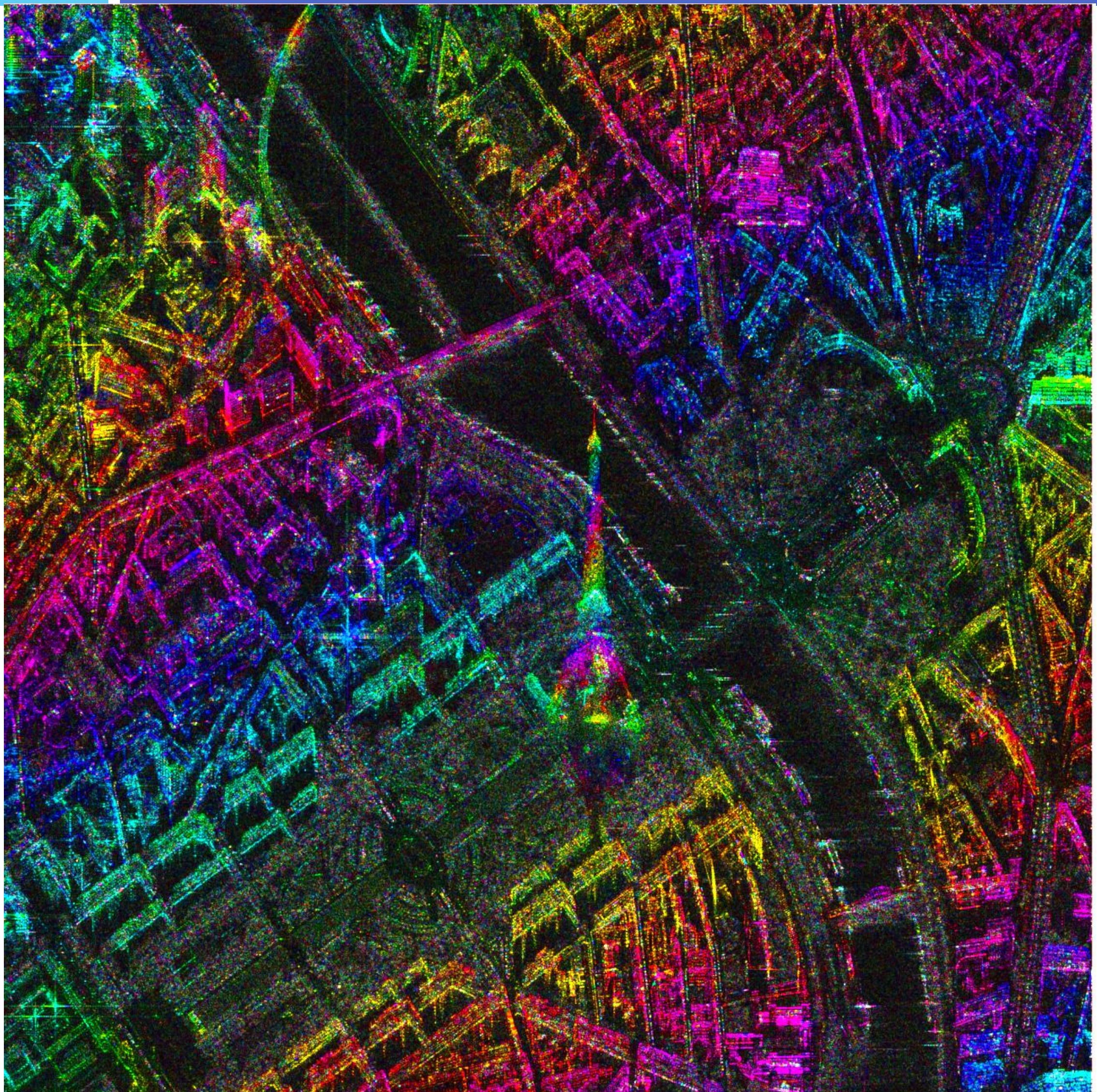
TSX stripmap/TSX spotlight
X-band
1mx1m 2mx6m



It still works…

- Between stripmap and spotlight
- And for a 18 month temporal baseline !

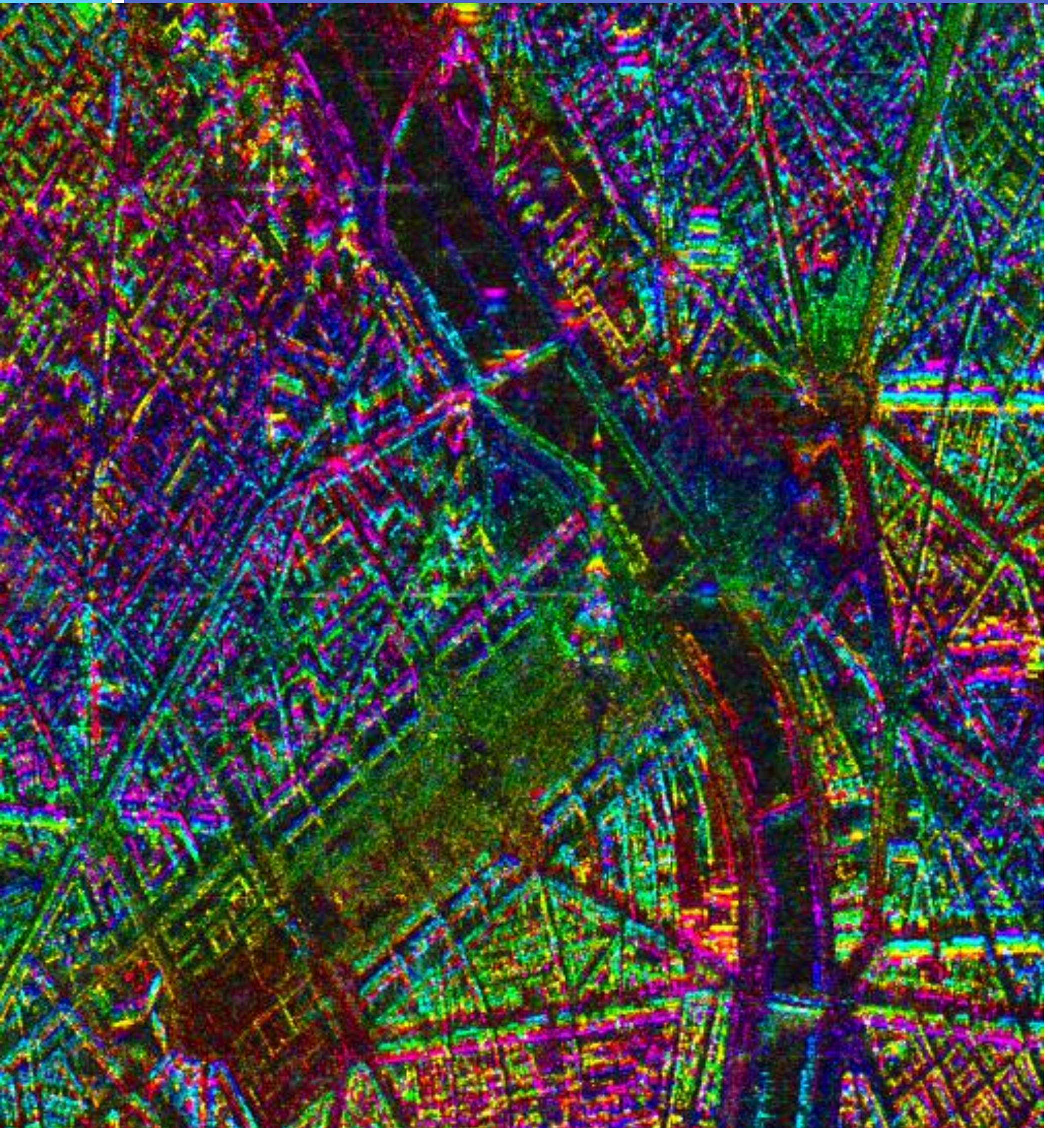
results on SAR interferometry : urban



- 2 spotlight TSM-X images: 1x1m
- 11 days

TSX spotlight
X-band
1mx1m

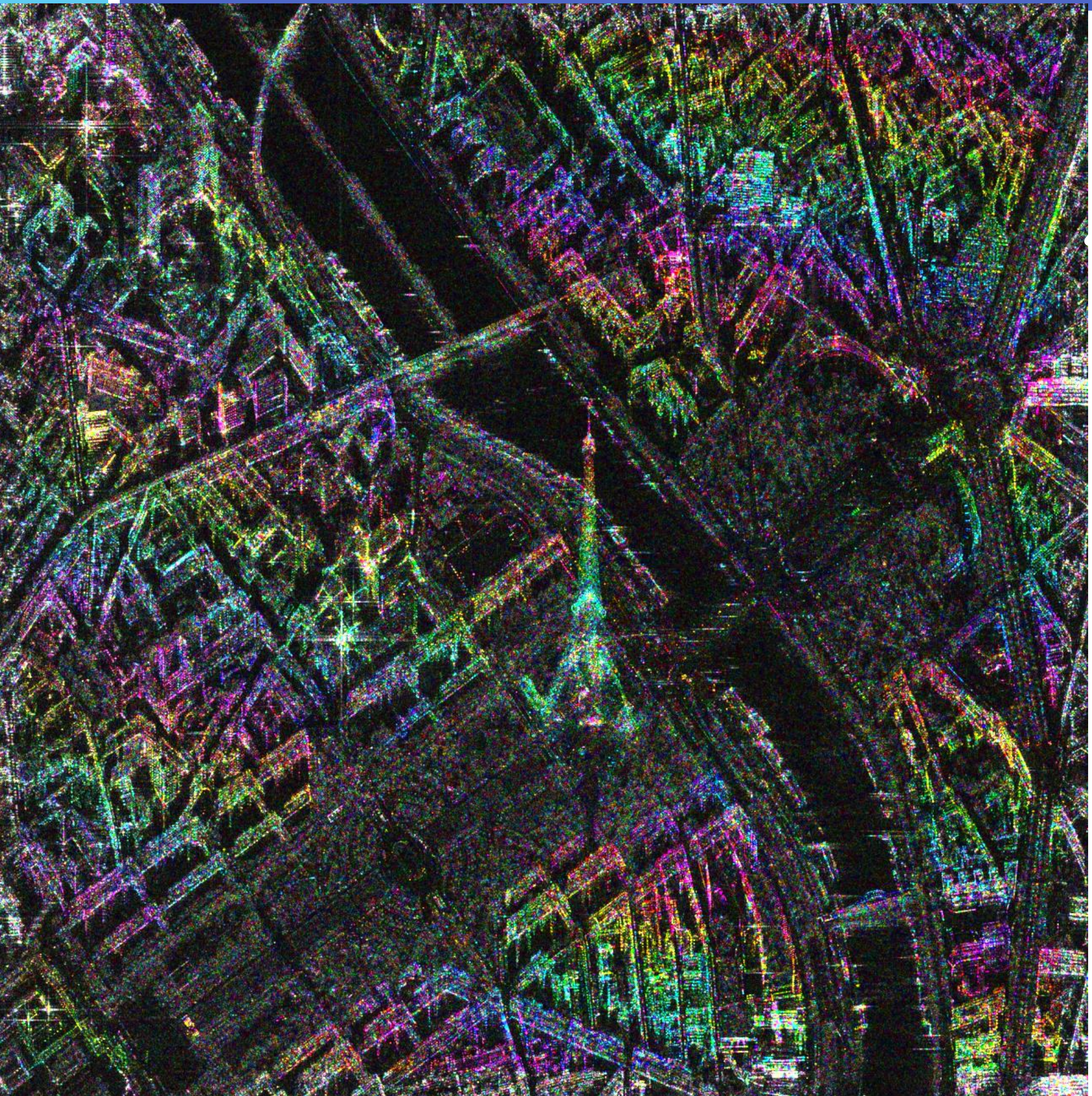
results on SAR interferometry: urban



TDX stripmap
X-band
1mx1m

- 2 stripmap TDM-X images: 2x2m
- 11 days

results on SAR interferometry: urban



TDX / TSX
stripmap
/spotlight
X-band

- 4 years !

optical / radar

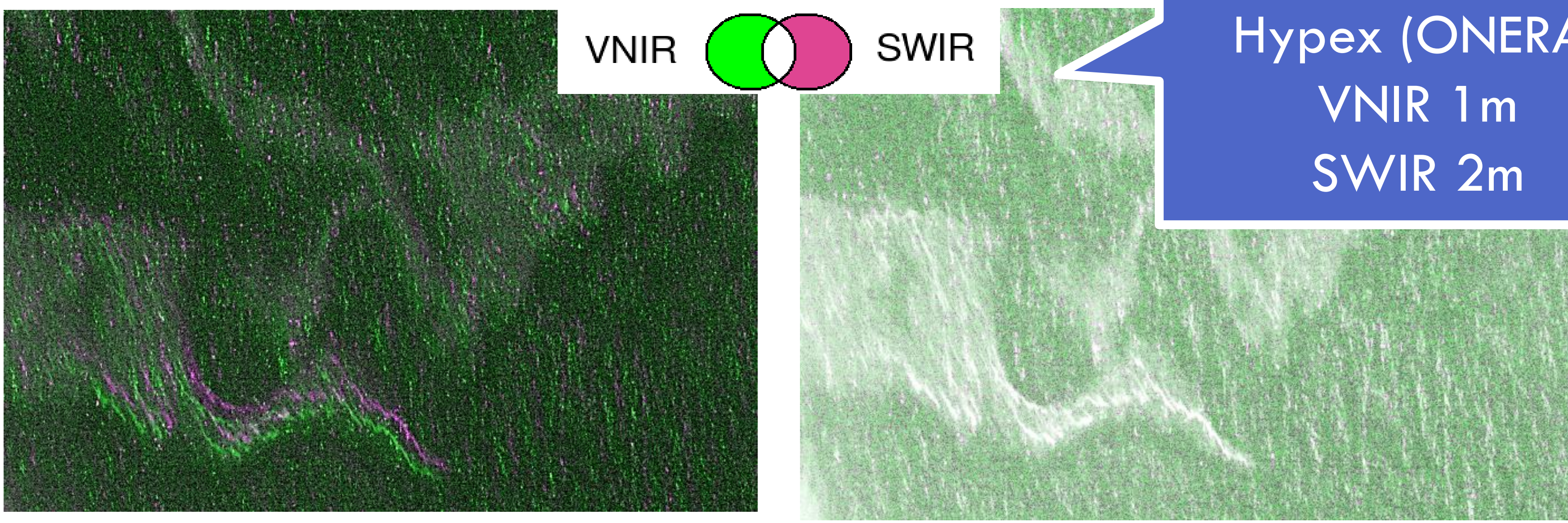
SAR SETHI 80cm
Airborne 50 cm

optical / radar

SAR SETHI 80cm
Airborne 50 cm

VNIR-SWIR: hyperspecral airborne images

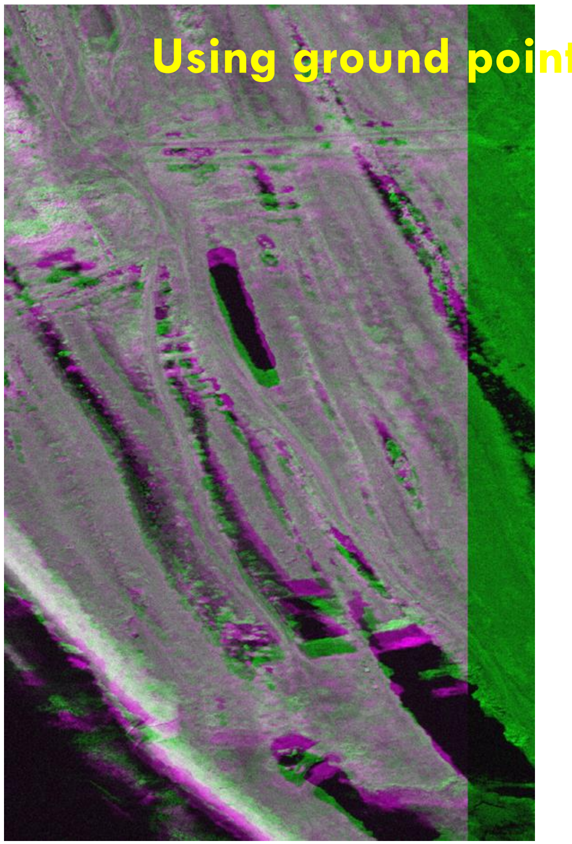
- Always try to choose closest frequency bandwidth



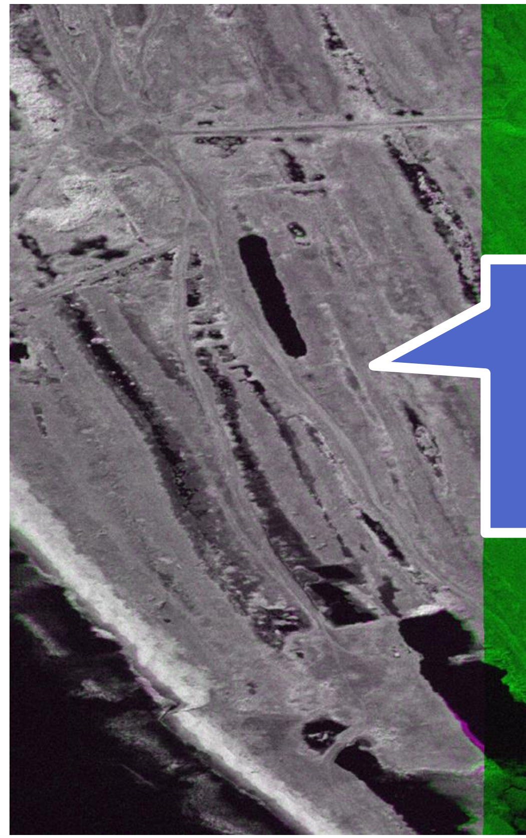
Hypex (ONERA)
VNIR 1m
SWIR 2m

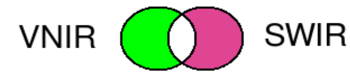
Here, a small radius (4) was necessary to achieve local deformations

VNIR-SWIR Master: VNIR



ZOOM

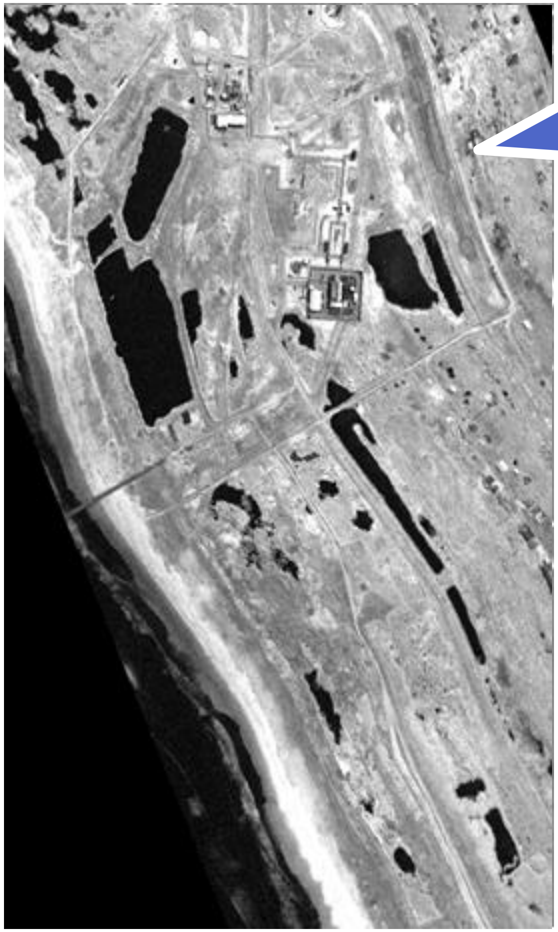




Hypex (ONERA)
VNIR 1m
SWIR 2m

To Compute the flow
Select the closest frequency bandwidths between VNIR and SWIR !

VNIR-SWIR Master: SPOT (Panchro)

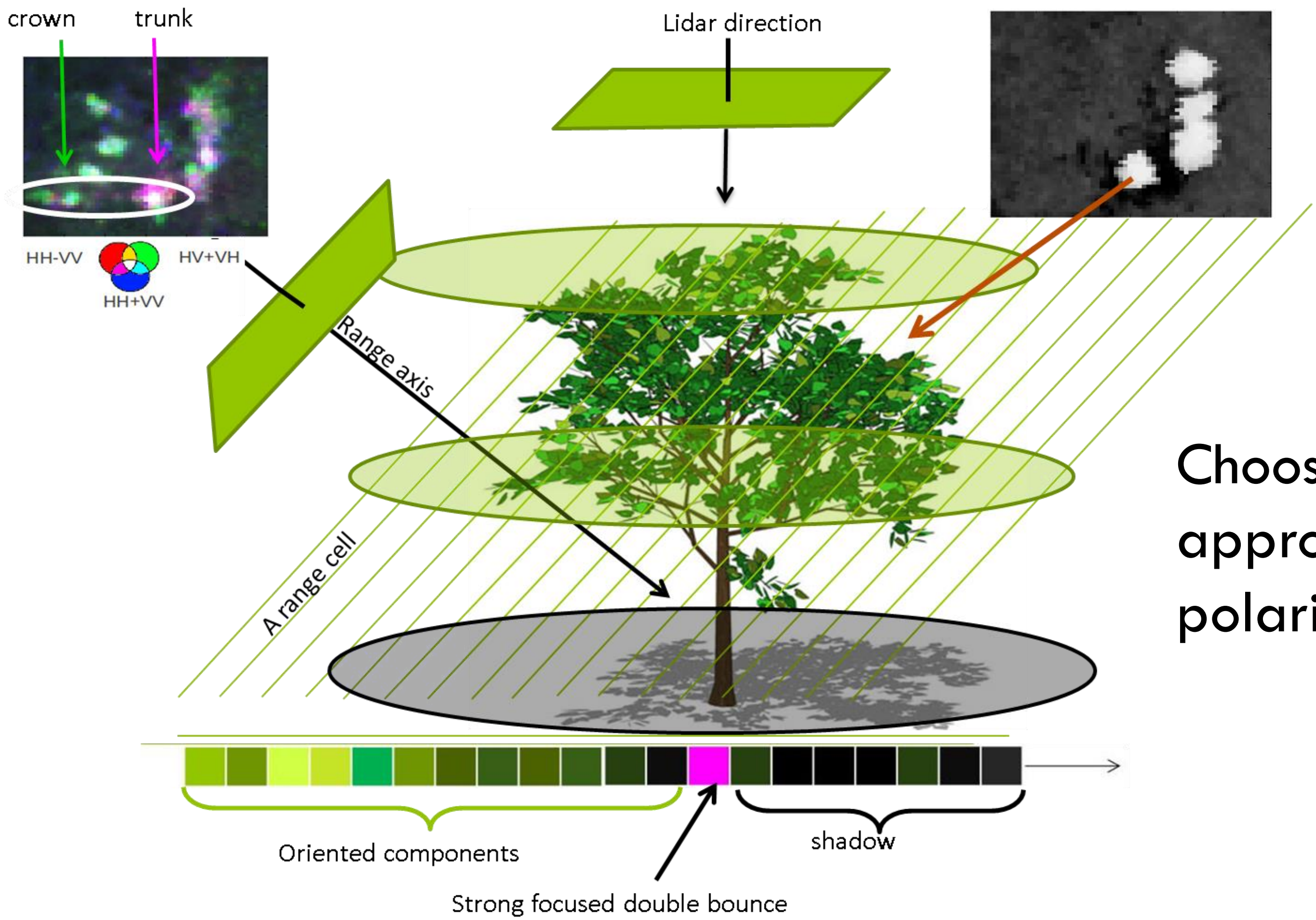


Hypex (ONERA)1m
SPOT 1.5m

To Compute the flow

Select the frequency bandwidth included in SPOT and sum the bands of VNIR together to get same frequence content.

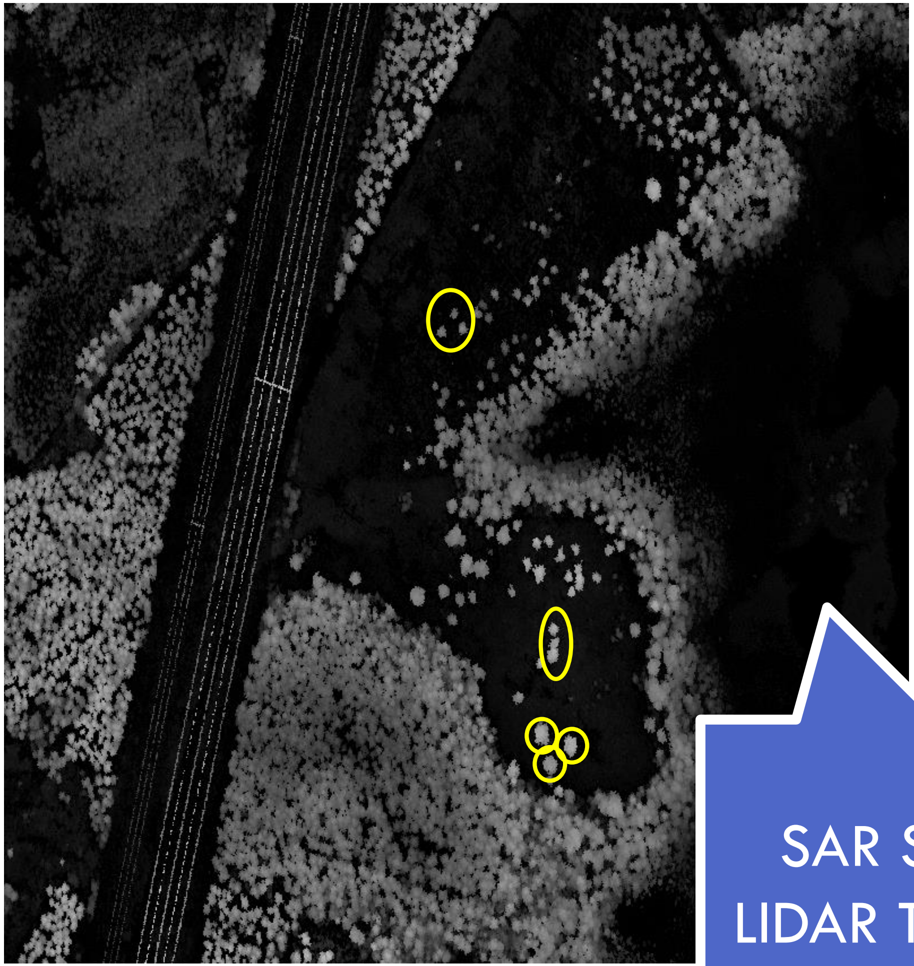
Results on SAR/LIDAR



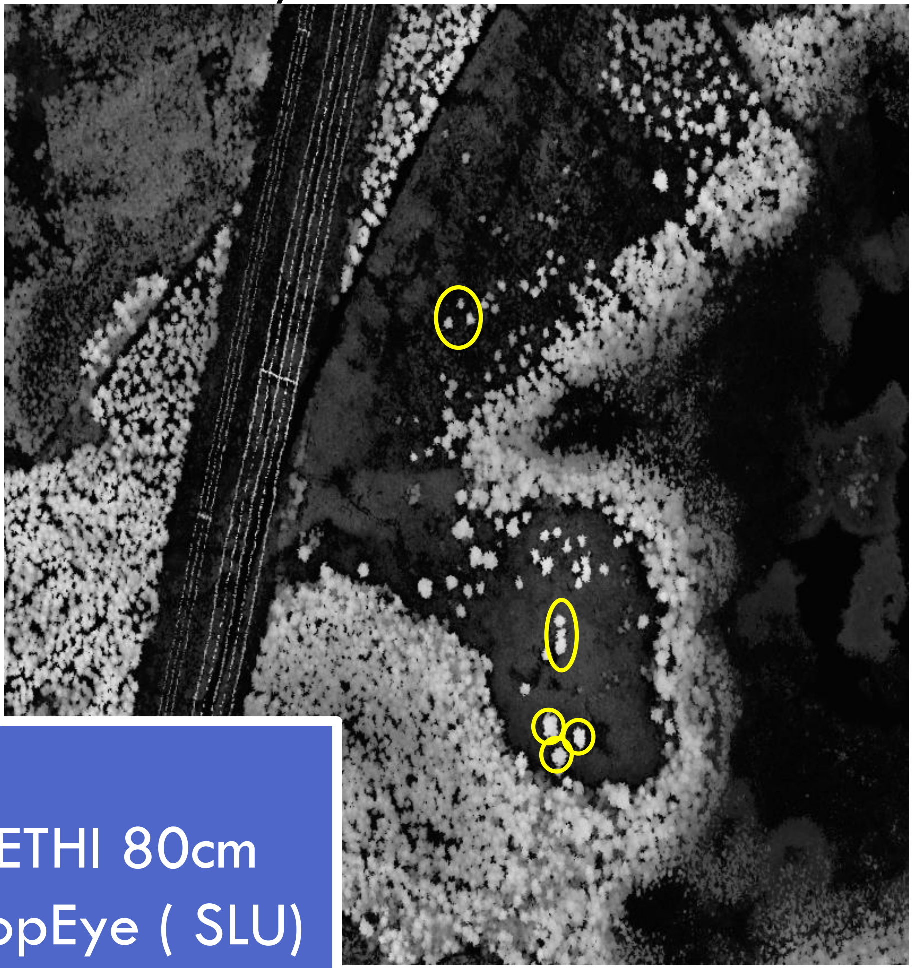
Choose the appropriate polarization (HH-VV)

Lidar / radar

By our best georeferencing



Refined by eFolki

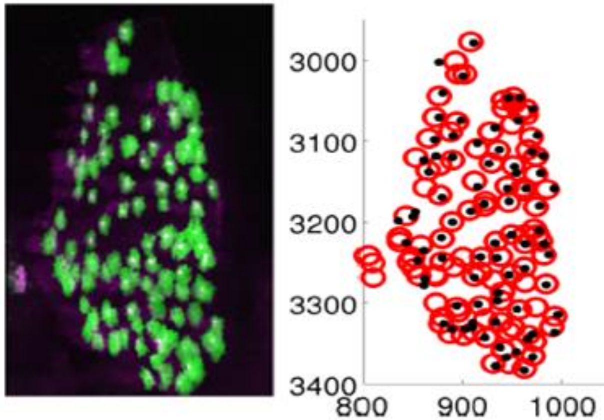


SAR SETHI 80cm
LIDAR TopEye (SLU)

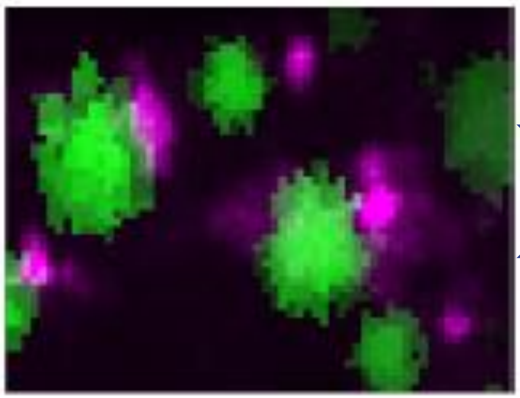
LIDAR / RADAR by georeferencing

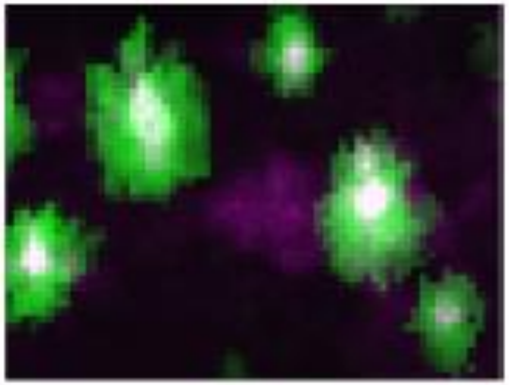

LIDAR / RADAR by eFolki

Quantitative results

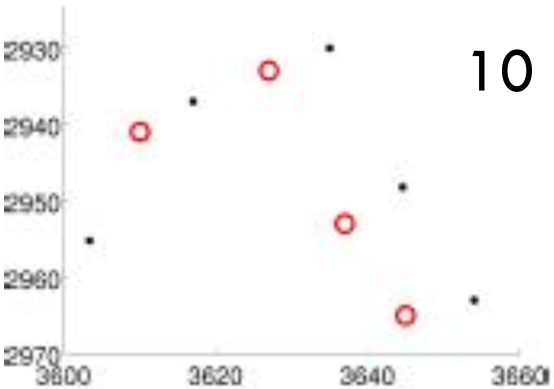


Statistics derived for several hundred of trees

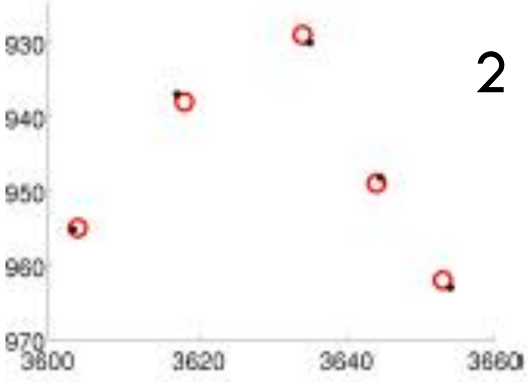




- Geocoding
- GeFolki



10 pixels



2 pixels

Precision x5

Conclusion

- Yes, it is possible to use an optical flow estimation to coregistrate remote sensing images
- It is better than georeferencing: Precision x5
- It is 10 times faster than an approach based on mutual information without GPU….with GPU: Speed x1000
- Without any auxilliary data

FUTURE WORK

- Automatic parameter fitting
- Use of different bands

Mode details?

November 2015, GRSL.

A new co-registration algorithm for recent applications on urban SAR images

Aurélien Plyer, Elise Colin-Koeniguer and Flora Weissgerber

Abstract—**In this paper a fast and robust optical-flow estimation algorithm is investigated for SAR images coregistration. The principle of the initial algorithm is described, as well as its adaptation to the case of radar images. A performance evaluation method is proposed to fix the choice of the parameters of the algorithm. Promising results in change detection or interferometry between SAR images of different resolutions are presented. They offers the opportunityto use this kind of algorithm in the case of high resolution images containing many structural elements as in urban areas.**

I. Introduction

Registration is a fundamental task in image processing used to match two or more images obtained, for example, at different times, from different sensors, or from different viewpoints. The precision required for this registration depends on the application [1], which may be change detection, interferometry, and fusion. The coregistration technics can be decomposed into several steps:

- coarse coregistrating two images at up to one or two pixels accuracy, after choosing a common spatial sampling.
- fine coregistrating, where we search the remaining transformation.
- fitting transformation equations
- resampling slave image according to the subpixel transformation.

In this paper we are interested only in the fine coregistration step, which can be seen as a flow estimation.

When external data such as orbits and Digital Elevation Model are available with required accuracy, then geometry-based appproaches can handle this problem [2]. Otherwise, when only images are used, the corresponding methods can be divided into two different categories: spatial methods and frequency domain methods.

- Spatial methods operate in the image domain, matching intensity patterns or features in images. Intensity-based methods compare intensity patterns in images via correlation metrics, while feature-based methods first find features such as points, lines, and contours, and match them between the images, as in [3].
- Frequency-domain methods find the transformation parameters while working in the transform domain for simple transformations, such as translation, rotation and scaling.

Phase correlation is a fast frequency-domain approach to estimate the relative translational offset between two similar monosensor images, that is robust to noise, occlusions and other typical defects of satellite images. Phase correlation techniques are often applied locally on a grid of points, to find their conjugate points which are in turn used to fit a polynomial surface to evaluate the deformation all over the image. However, performance is degraded around motion boundaries or depth discontinuity areas, which is also a challenge to most of the existing motion estimation methods. Moreover, the applications encountered become increasingly challenging. This is the case, for example, for:

- close images in non-interferometric conditions, whose deformation between images depends on terrain elevation, and which does not necessarily fit to a simple surface model;
- images with very severe decorrelation, for example images at X-band with several years of revisit time, making precise coregistration a non trivial task;
- images acquired in different SAR modes (stripmap, spotlight) with different resolutions and speckle patterns.

In this paper we show how a cutting edge optical flow called eFolki could be applied to SAR processing and how the quality of co-registration in precision and robustness open the door to generation of new results in high resolution of SAR images of urban areas. Here, the displacement is evaluated for each pixel and does not require to select control points or grid points. The step of polynomial regression is not required, and the algorithm therefore adapts to any kind of displacement between the two images, even in the case of high relief. Despite of a pixel by pixel approach, the algorithm is still fast because its computing time has been optimized.

We start by introducing briefly the main properties of eFolki optical flow and why it is well suited to SAR images co-registration. Then we present two main applications who take advantage of the performance of eFolki. First we apply the method to SAR-SAR change visualization at different resolutions, where pixel precision of the registration is crucial to good change visualization without artefacts. Secondly we use eFolki for interferometry. In particular we are able to co-register a high resolution spotlight TerraSAR-X image with a stripmap one of different resolution and to produce the corresponding interferogram.

II. The eFolki algorithm for SAR coregistration

In this section we will give a short description of the algorithm in order to understand which parameters have to be adapted to the case of SAR images. eFolki is a fast and robust optical flow estimation technique derived from the Lucas-Kanade [4] (LK) gradient-based approach. eFolki [5] algorithm takes its roots in the FOLKI optical-flow estimator

June, 2016 JSTARS

Adaptation and Evaluation of an optical flow method applied to co-registration of forest remote sensing images

Guillaume Brigot, Elise Colin-Koeniguer, Aurélien Plyer, Fabrice Janez

Abstract—**The coregistration of heterogeneous geospatial images is useful in various remote sensing applications. Since the number of available data increases and the resolution improves, it is interesting to have an approach as automated, fast, robust and accurate as possible. In this paper, we present a solution based on optical-flow computation. This algorithm called GeFolki allows the registration of images in a non-parametric and dense way. GeFolki is based on a local method of optical flow derived from the Lucas-Kanade algorithm, with a multi-scale implementation, and a specific filtering including rank filtering, rolling guidance filtering and local contrast inversion. The efficiency of our coregistration chain is shown on radar, LIDAR and optical images on Remningstorp forest in Sweden. An analysis of the relevant parameters is investigated for several scenarios. Finally, we demonstrate the accuracy of our coregistration by proposing specific metrics for LIDAR/radar coregistration, and optic/radar coregistration.**

I. Introduction

Coregistration of heterogeneous images is useful in various remote sensing image fusion applications, since one expects a gain from the synergy of sensors. Applications where data fusion is relevant are numerous, whether for land classification [1], for agriculture [2], or forestry applications. In the case of the forest, many works illustrate the benefit of the combination of LIDAR and radar images [3], [4], LIDAR and high resolution optical images [5], or radar and optical images [6], [7], for the characterization of plant species or biomass assessment.

In all cases where the expected product is a map, geometrically aligning two or more images in order to combine pixels corresponding to the same objects is a crucial step of the fusion.

Most methods of remote sensing image coregistration are based either on geocoding, or on non-rigid image registration methods that use only the images as input.

In the case of geocoding, the accuracy of coregistration will be highly dependent on the availability and precision of both a DTM (Digital Terrain Model) and the orbit parameters [8].

On the other hand, non rigid image registration without geocoding is widely investigated in various fields beyond the scope of remote sensing, for example in computer vision and medical imaging [9]. In computer vision, video image co-registration has to meet the constraints of robustness and speed of execution, but often focuses on images taken from the same sensor with little delay in time. In medical imaging [10] or remote sensing, difficulty generally lies in the different nature of the images to compare. Moreover, the context of remote sensing is also changing today with larger quantities of time series data, and some time-sensitive applications require fast processing. This is the case for example for near real time change detection for rapid post disaster assessment, wildlife tracking, and surveillance across broad areas such as battlefields or border regions [11].

Most non-rigid registration methods are *parametric methods*, meaning that an assumption is made about a parametrized model that constrains the form of the expected deformations between processed images. Then a similarity function is optimized to find an approximation of a real underlying deformation [12]. Among them, feature-based approaches establish a correspondence between a number of especially distinct points in images [13]. Selection of these points can use SIFT [14], [15] or SURF methods [16]. Other methods handle more complex features, such as segments, or use the shape descriptors [17], [18].

The choice of an image similarity measure is a key point. One of the most widespread used for the registration of multimodality images is mutual information [19]. Already used in remote sensing image coregistration, the main drawback of this measure is that it is quite time consuming. Instead of employing a similarity metric, [20] proposes to exploit a low rank constraint to jointly register multiple hyper-spectral images. Although such a model appears to be stable with respect to occlusions and imaging artifacts, it is not directly applicable in our case. In practice such a model requires a stack of multiple images and is further quite slow.

Another family of non-rigid coregistration methods are *non-parametric*. Among them, *dense* methods compute a displacement for every pixel in the image. They are particularly interesting in the case of very local deformation due for example to terrain elevation that has a lot of influence on high resolution images. Most of dense and non parametric methods belong to *optical flow* estimation. Optical flow is the pattern of apparent motion of objects in a visual scene caused by the relative motion between the sensor and the scene. Optical flow methods have been developed in a context where the constraints of speed and robustness to environmental effects have led to intensive efforts in producing algorithms that combine robustness, precision and high computing speed.

In this paper, we want to show how one optical flow method can undertake such a task of co-registration of heterogeneous images.

Optical flow has already been considered by the remote sensing community. [21] proposes a dense method to reconstruct the annual motion of glacier surfaces from ortho-photos.

Practical Exercices

- TP1 : Optic / Optic : Worldview and Quickbird
- TP2 : Lidar / SAR : (airborne) TopEye (SLU)/SETHI (Onera)
- TP3 : Optic / SAR (airborne) SLU/SETHI
- TP4 : SAR/SAR (airborne) SETHI/SETHI

- Images are in Dataset Directory

Command lines

- **Python:**

```
u, v = EFolki(Array1, Array2, iteration=nblevel, radius=[ , ], rank=r , levels= )
u, v = GEFolki( ….)            (with contrast inversion)
```

- **Matlab:**

```
para = struct('radius' ,[16,8], …
        'levels' , nblevel−1, …
        'iter' , , …
        'contrast_adapt', false, …
        'rank',r);
W=GeFolki(im1,im2,para);
```

Common errors

- Apply same mask filled with zero when images do not cover the same area
- Remove NaN