Remote Sensing Laboratory
University of Trento – Fondazione Bruno Kessler
Via Sommarive, 5-18, I-38123 Povo, Trento, Italy

FINE CO-REGISTRATION OF VHR IMAGES FOR MULTITEMPORAL URBAN AREA ANALYSIS

Youkyung Han
Francesca Bovolo
Lorenzo Bruzzone

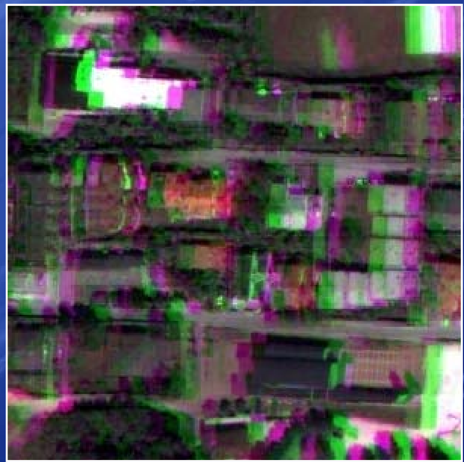
E-mail: youhan@fbk.eu
Web page: http://rslab.disi.unitn.it

Outline

Introduction

- ✓ Image co-registration is the process of spatially overlaying images acquired over the same areas at different times.
- ✓ Poor misalignment results in Registration Noise (RN), which is a critical source of errors when performing multitemporal information extraction.


Original QuickBird image

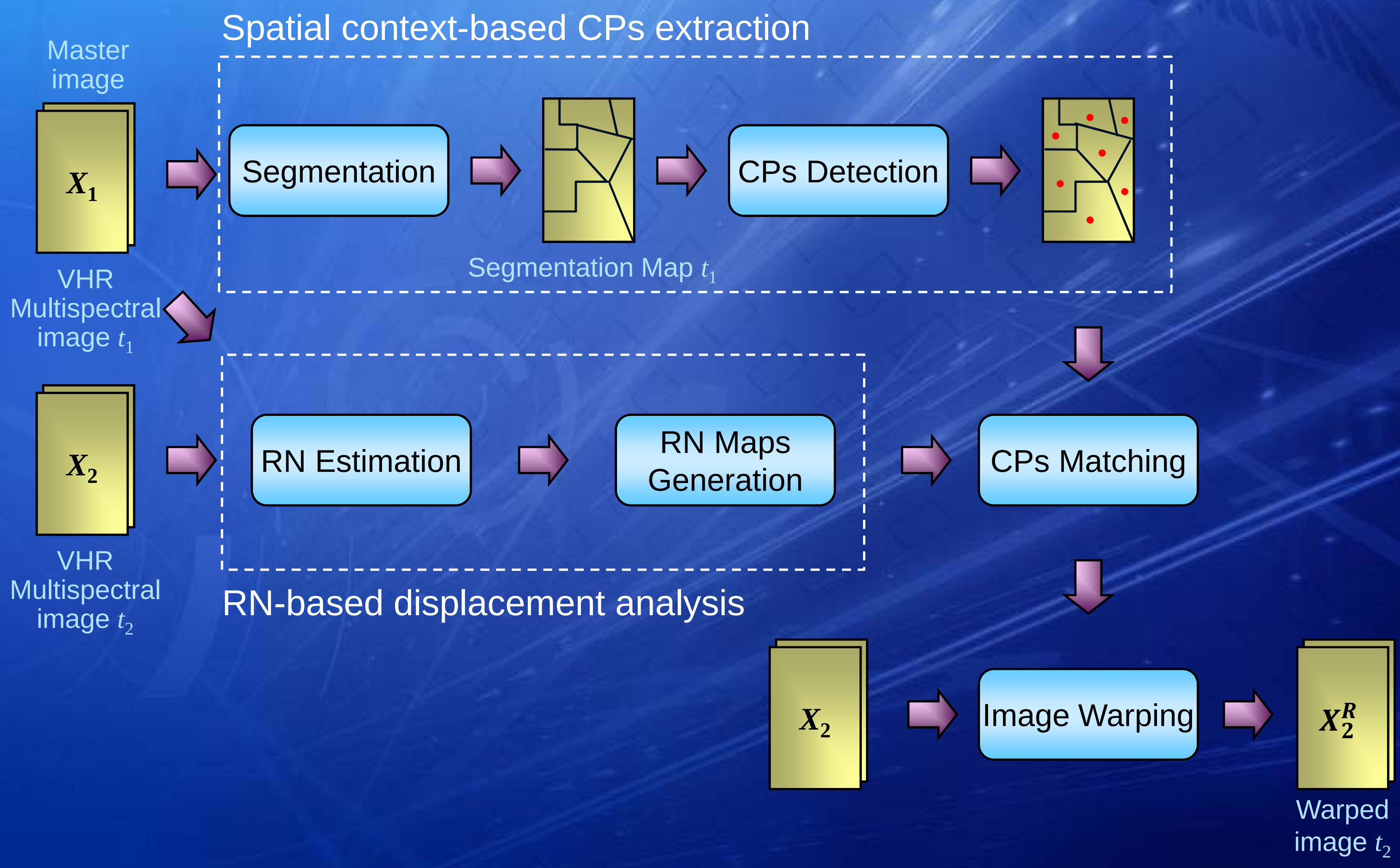

Multitemporal false-color composite

Open issue: Even after effective state-of-the-art co-registration, Very High Resolution (VHR) multitemporal images show a residual misalignment due to local effects such as differences in the acquisition conditions (e.g., view angle of the sensor, acquisition geometry).

Aim of the Work

- ✓ Design a method for fine automatic co-registration of multitemporal VHR images that reduces the impact of residual Registration Noise (RN) and thus improves co-registration accuracy.
- ✓ The proposed method:
  - Refines the result of standard state-of-the-art co-registration methods.
  - Extracts spatial context-based Control Points (CPs).
  - Exploits RN properties for identifying and reducing the residual local misalignment.
  - Establishes the correspondence of CPs according to local misalignment.
- ✓ Test the proposed method on simulated and real multitemporal VHR images.

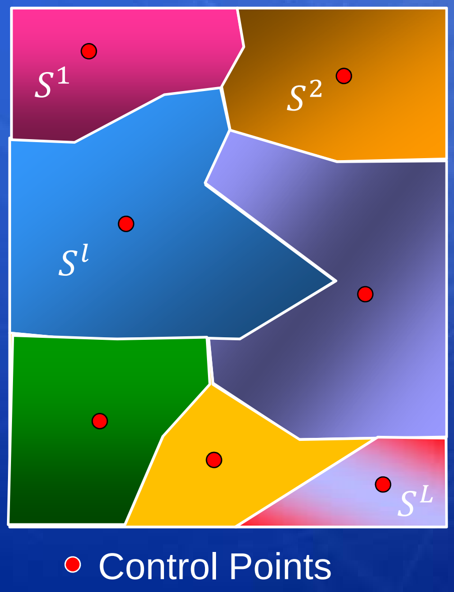
Proposed Approach: Block Scheme



Spatial Context-based CPs Extraction

Basic assumption: homogeneous areas and objects are locally affected by similar distortions.

Goal: Identify CPs that are representative of objects and account for their spatial context properties.



Segment the master image X_1, and use centroids of segments as CPs under the assumption that they are representative for each segment.

$$\bigcup_{l=1}^{L} S^l = X_1 \text{, with } S^m \cap S^n = \emptyset, n \neq m$$

$$H\left(S^l(x,y)\right) = true \;\; \forall (x,y) \in S^l$$

homogeneity measure

$$H(S^m \cup S^n) = false \;\; \forall S^m \text{ and } S^n \text{ adjacent}$$

RN-based Displacement Analysis

Goal: Use Registration Noise information to estimate the amount of local displacement.

Working hypotheses:

- ✓ Under the assumption that Images X_1 and X_2 are co-registered the residual misalignment can be modeled by small rigid translation effects only;
- ✓ Different portions/objects in the considered scene may be affected by different local misalignments.

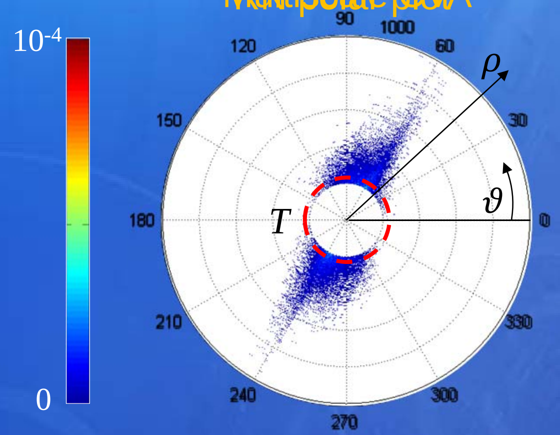
Definitions:

- ✓ Let $\Omega = \{\Omega_1, \ldots, \Omega_d, \ldots, \Omega_D\}$ $(\Omega_d = \{\Delta x_d, \Delta y_d\})$ be the set of possible D displacements.
- ✓ Let $X_2^D = \{X_2^d, d = 1, \ldots D\}$ be the set of slave images X_2 after applying displacements in Ω.

RN-based displacement analysis

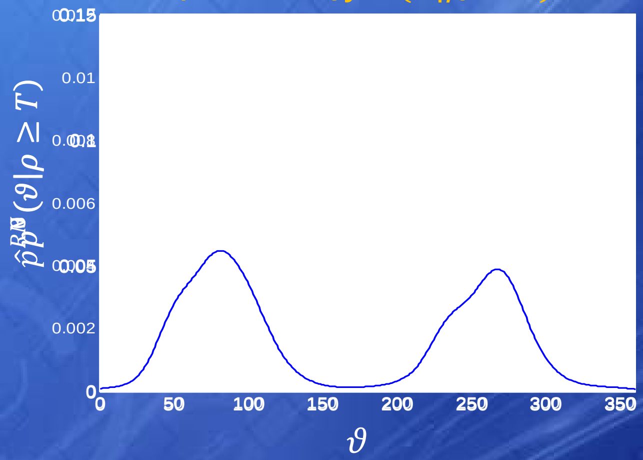
Step 1: for each pair (X_1, X_2^d) and $\Omega_d \in \Omega$ compute RN map M_d $(d = 1, \dots, D)$.

RN polar plot

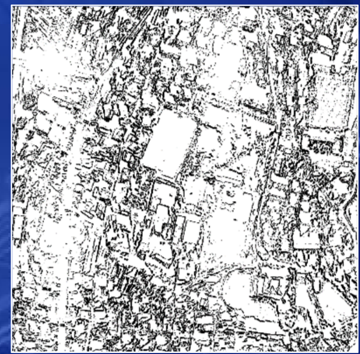


$X_D^{\vartheta} = X_2^{\vartheta} - X_1^{\vartheta}$

RN probability density function



Registration Noise



Constant

Magnitude variable

Direction variable

RN pdf

$$\hat{p}^{RN}(\vartheta|\rho \geq T) = C[P^0(\rho \geq T)\hat{p}^0(\vartheta|\rho \geq T) - P^N(\rho \geq T)\hat{p}^N(\vartheta|\rho \geq T)]$$

RN map for the d-th misalignment

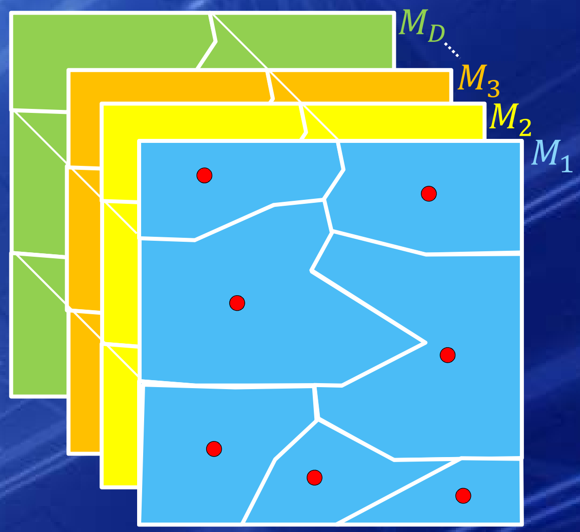
Threshold for RN distribution

$$M_d(x,y) = \begin{cases} 1, & \text{if } \hat{p}_d^{RN}(\vartheta_d(x,y)|\rho_d(x,y)) \geq T_{RN} \\ 0, & \text{otherwise} \end{cases} \quad \forall\ d = 1, \dots D$$

F. Bovolo, L. Bruzzone and S. Marchesi, "Analysis and adaptive estimation of the registration noise distribution in multitemporal VHR images," IEEE Transactions on Geoscience and Remote Sensing, vol. 47, no. 8, pp. 2658–2671, 2009.

RN-base displacement analysis

Step 2:



- ✓ Perform local analysis by dividing each RN map M_d $(d = 1, \ldots, D)$ into the L segments computed on X_1.
- ✓ For each segment and pair $(X_1,\ X_2^d)$ estimate the amount of misaligned pixels (AM_d^l):

RN pixels for the l-th split and d-th misalignment

$$AM_d^l = \sum_{(x,y)\in S^l} M_d^l(x,y) \qquad \forall \quad \begin{array}{l} l = 1, \ldots, L \\ d = 1, \ldots, D \end{array}$$

CPs matching

- ✓ Each segment S^l is associated to the local displacement $\Omega^l \in \Omega$ that minimizes the local residual misalignment for on the (X_1, X_2^d) pairs:

$$\forall \; S^l \in S \quad \Omega^l = arg \min_{\Omega_d \in \Omega} \{AM_d^l\}$$

- ✓ The m-th corresponding CP pair $\{(x_{1,l}^m, y_{1,l}^m)$, $(x_{2,l}^m, y_{2,l}^m)\}$ in the l-th segment is defined as:

$$\begin{cases} x_{2,l}^m = x_{1,l}^m - \Delta x_l \\ y_{2,l}^m = y_{1,l}^m - \Delta y_l \end{cases} \quad \forall l = 1, \dots, L; \;\; \forall m = 1, \dots, M$$

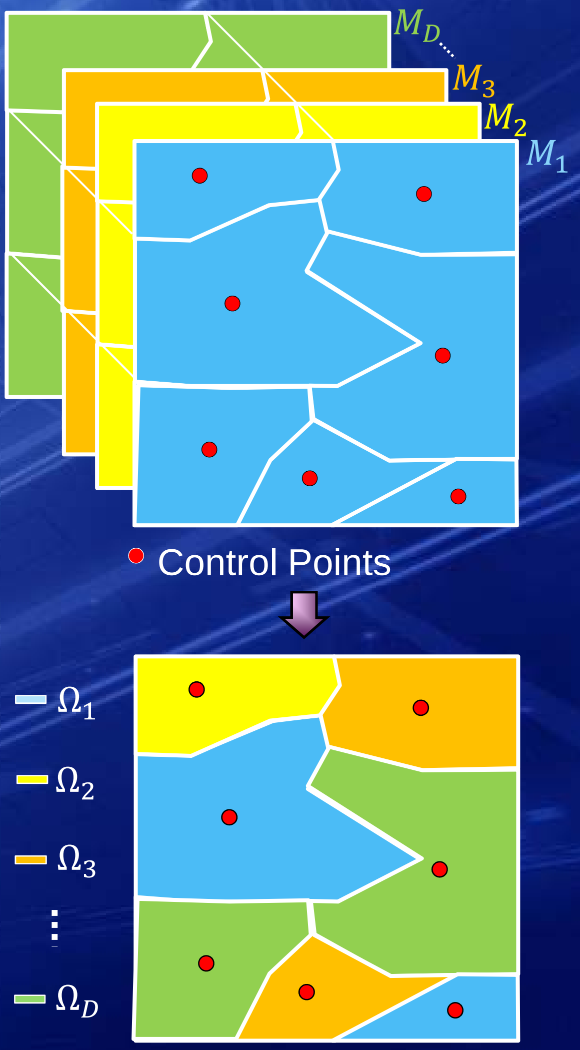


Image warping

- ✓ Remove inconsistent CPs due to uncertainty factors (e.g., shadows), by evaluating geometric consistency:

  i. Estimation of affine transformation using all CPs.

  ii. Removal of CP pairs having large Root Mean Square Error (RMSE).

  The process ends when all the remaining CP pairs have RMSE smaller than a threshold T_{RMSE}.

- ✓ Perform warping by the piecewise linear function M_{PL} to effectively mitigate local distortions by a non-rigid transformation.

- ✓ M_{PL} is constructed on all CP pairs and applied to warp the slave image X_2 to spatial coordinates of master image X_1 as:

$$X_2^R = M_{PL}(X_2).$$

Experimental Results: Simulated dataset

Study area: City of Trento, Italy.

Master image (X_1):
- pansharpened QuickBird image;
- acquired in October 2005;
- 1000x1000 pixels.

Slave image (X_2): Distorted X_1 image
- x direction: $u = x - 4\sin(0.5\pi x + 150)$;
- y direction: $v = y + 3\sin(0.5\pi y + 200)$.

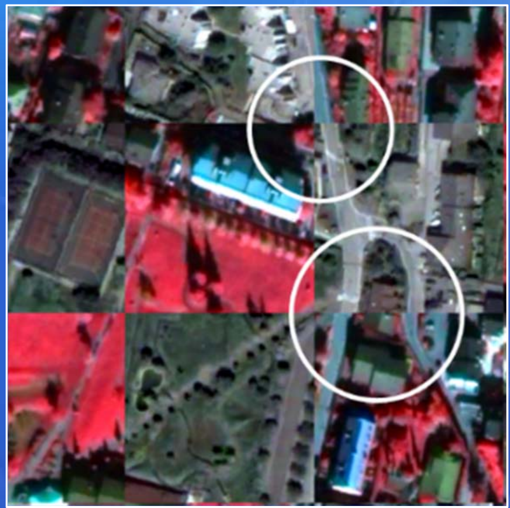
Goal:
- Validate the effectiveness of the proposed method in performing co-registration.

Average segments area: 500 m^2

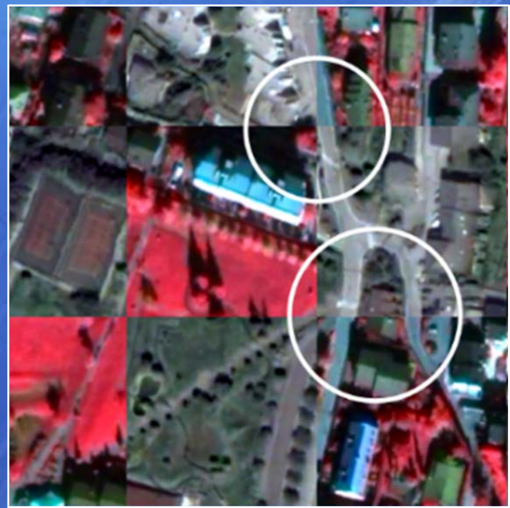
Master image (X_1)

Experimental Results: Simulated dataset

Chessboard images



No registration



Proposed approach

	X_1	X_2
R	Red	NIR
G	Green	Red
B	Blue	Green

Registration method	Correlation Coefficient	Normalized Mutual Information
No registration	0.810	0.634
State of the art approach[2]	0.811	0.660
Proposed approach	0.969	0.924

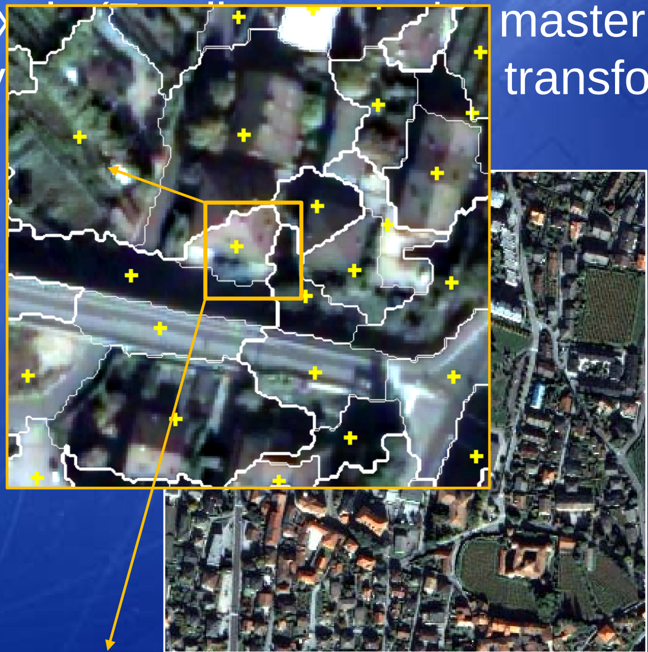
[2] Y. Han, J. Choi, Y. Byun and Y. Kim, "Parameter optimization for the extraction of matching points between high-resolution multisensor images in urban areas," IEEE Transactions on Geoscience and Remote Sensing, vol. 52, no. 9, pp. 5612–5621, 2014.

Experimental Results: Real dataset

Master image (X_1): a 1000×1000 pixels pansharpened QuickBird image acquired in October 2005.

Slave image (X_2):

- ✓ Pansharpened QuickBird image (July 2006);
- ✓ 1200×1200 pix … master image);
- ✓ Pre-aligned by … transform (SIFT)-based method[2].



Shadows

Mixed segments

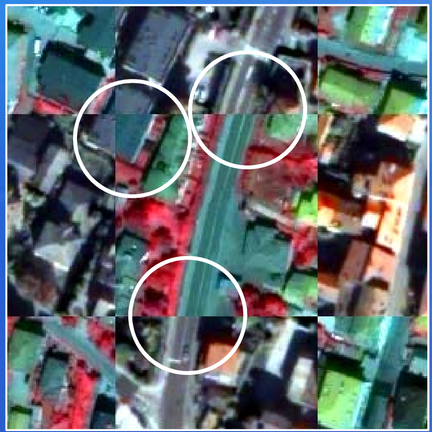
Master image (X_1)

Slave image (X_2)

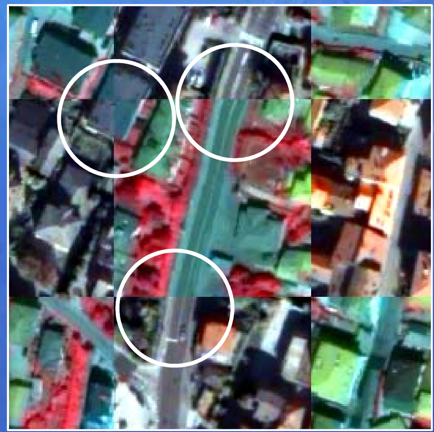
[2] Y. Han, J. Choi, Y. Byun and Y. Kim, "Parameter optimization for the extraction of matching points between high-resolution multisensor images in urban areas," IEEE Transactions on Geoscience and Remote Sensing, vol. 52, no. 9, pp. 5612–5621, 2014.

Experimental Results: Real dataset

Chessboard images



State of the art approach



Proposed approach

	$\mathbf{X}_1$	$\mathbf{X}_2$
R	Red	NIR
G	Green	Red
B	Blue	Green

Registration method	**RMSE (pixels)**	**RMSE STD (pixels)**
No registration	25.51	2.03
State of the art approach	3.70	2.21
Proposed approach	1.39	0.65

Parameters		**Values**
Spectral bands		Red & NIR
Multiscale level N		4
Threshold	magnitude T	Automatic selection
	RN density T_{RN}	10^{-4}
	RMSE T_{RMSE}	10
Displacements Ω_d		[-5, +5]
Sampling interval of Ω_d		0.5
Manually selected checkpoints		20

Conclusion

- ✓ A fine co-registration method for VHR multitemporal images that improves co-registration accuracy of images already geometrically pre-aligned by standard methods has been proposed.

- ✓ The proposed method uses spatial context-based CPs to exploit the spatial correlation of pixels in VHR images and prevent inhomogeneous distribution of CPs.

- ✓ The proposed method effectively mitigates the local residual misalignment by exploiting the properties of RN to estimate the local misalignment of CPs.

- ✓ The proposed method improved the co-registration accuracy over the considered state-of-the-art methods both in simulated and real datasets.

Future developments

- ✓ Improve the mechanism to reduce and handle CPs inconsistencies due to:
  - Uncertain factors (e.g., shadow areas, occlusions);
  - The presence of non completely homogeneous segments.

- ✓ Extend the use of the proposed context-based fine co-registration method to VHR multispectral images acquired by different sensors.