

# A New Coregistration Algorithm for Recent Applications on Urban SAR Images

Aurélien Plyer, Elise Colin-Koeniguer, and Flora Weissgerber

**Abstract**—In this letter, a fast and robust optical-flow estimation algorithm is investigated for synthetic aperture radar (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 offer the opportunity to use this kind of algorithm in the case of high-resolution images containing many structural elements as in urban areas.

**Index Terms**—Image fusion, image registration, radar interferometry, synthetic aperture radar (SAR).

## 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 techniques can be decomposed into several steps:

- coarse coregistering two images at up to 1- or 2-pixel accuracy, after choosing a common spatial sampling;
- fine coregistering, where we search the remaining transformation;
- fitting transformation equations;
- resampling slave image according to the subpixel transformation.

In this letter, 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 (DEM) are available with required accuracy, then geometry-based approaches can handle this problem [2]. Otherwise, when only images are used, the corresponding methods can be divided into two different categories, namely, spatial methods and frequency-domain methods.

- Spatial methods operate in the image domain, matching intensity patterns or features in images. Intensity-based

Manuscript received February 17, 2015; revised May 18, 2015 and June 23, 2015; accepted July 6, 2015. Date of publication August 14, 2015; date of current version October 27, 2015.

A. Plyer and E. Colin-Koeniguer are with the Département Traitement de l’Information et Modélisation, ONERA, 91123 Palaiseau Cedex, France (e-mail: aurelien.plyer@onera.fr; elise.koeniguer@onera.fr).

F. Weissgerber is with ONERA, 91123 Palaiseau Cedex, France and also with the Département Traitement du Signal et des Images, Télécom ParisTech, 75013 Paris, France (e-mail: flora.weissgerber@onera.fr).

Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/LGRS.2015.2455071

methods compare intensity patterns in images via correlation metrics, whereas 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, which 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 the following:

- 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 nontrivial task;
- images acquired in different synthetic aperture radar (SAR) modes [stripmap (SM) and spotlight (SL)] with different resolutions and speckle patterns.

In this letter, we show how a cutting-edge optical flow called eFolki could be applied to SAR processing and how the quality of coregistration in precision and robustness opens 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 a pixel-by-pixel approach, the algorithm is still fast because its computing time has been optimized.

We start by briefly introducing the main properties of eFolki optical flow and why it is well suited to SAR images’ coregistration. Then, we present two main applications that 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 artifacts. Second, we use eFolki for interferometry. In particular, we are able to

coregister a high-resolution SL TerraSAR-X image with an SM image of different resolution and to produce the corresponding interferogram.

## II. 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. eFolk is a fast and robust optical-flow estimation technique derived from the Lucas–Kanade [4] (LK) gradient-based approach. eFolk [5] algorithm takes its roots in the FOLKI optical-flow estimator developed in the domain of computer vision [6]. This algorithm found many successful application domains as in the particle imaging velocimetry domain [7] for wind tunnels’ fluid velocimetry where high precision and high compute scalability are important to process huge amount of data.

eFolk has a remarkably simple and parallel structure, which makes it ideally suited to massively parallel computing architectures in order to handle large images. The eFolk complexity and runtime are fully linear with respect to the pixel number. Due to this fact, the actual implementation could perform computation at a cost of 6 ms by megapixels with a linear cost in the number of pixels. For example, for a registration of all pixels of a  $10\,000 \times 10\,000$  image, this takes only 600 ms on a Titan GPU.

### A. Description of the Algorithm

For simplicity, we start to describe the FOLKI optical flow and introduce the eFolk modifications, and we end by a study of the main parameters of this algorithms and their role in the case of SAR images. A deeper justification with regard to the different parts of eFolk algorithm is available in [5].

Let us consider the registration of two images  $I_1$  and  $I_2$  defined on a 2-D support  $S \in R^2$ . What is called the dense optical flow in optics corresponds to the displacement to find between both images. It is defined by  $u : x \rightarrow u(x) \in R^2$ . The LK algorithm belongs to local or window-based approaches where  $u(x)$  is defined as the minimizer of a criterion computed over a local window centered on  $x$

$$J(u; x) = \sum_{x' \in S} \omega(x' - x) (I_1(x') - I_2(x' + u(x)))^2 \quad (1)$$

where  $\omega$  is a separable weighting function, uniform or Gaussian, of limited support  $\omega$ .  $\omega$  is typically a square  $(2r + 1) \times (2r + 1)$  window parameterized by its radius  $r$ .

Minimization is done by an iterative Gauss–Newton strategy based on first-order Taylor expansion of the intensity of image around a previous guess of the displacement  $u_k$ . This strategy makes LK a gradient-based approach, as opposed to block matching by exhaustive search over a limited area. Moreover, modern LK algorithms are not only iterative but also multiresolution as they use a pyramid of images to compute  $u$  at varying scales following a coarse-to-fine strategy.

In eFolk, two main modifications are introduced. First, (1) is modified to

$$J(u; x) = \sum_{x' \in S} \omega(x' - x) (R(I_1)(x') - R(I_2)(x' + u(x)))^2 \quad (2)$$

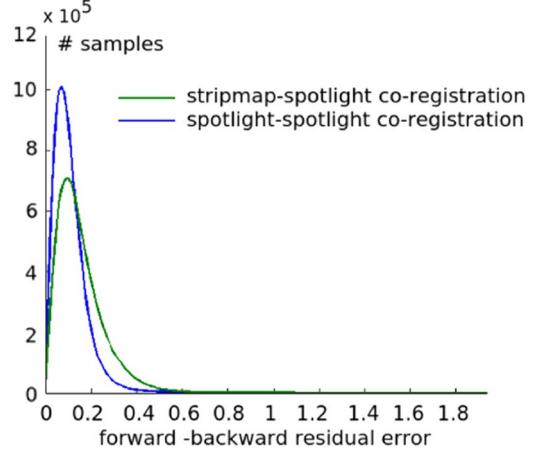


Fig. 1. Forward–backward distribution flow error for two cases using eFolk. The green curve is for the coregistration of SM and SL images and high temporal baseline. The blue curve is for the coregistration of two SL images and small temporal baseline.

where  $R(I)$  is a rank function applied to the image  $I$  based on the local gray-level ordering to compute the filtered value. It is expressed as

$$R(I)(x) = \# \{x' : x' \in S_R(x) \text{ with } |I(x)| > |I(x')|\} \quad (3)$$

where  $S_R(x)$  is a neighborhood of the pixel  $x$ .

The effect of the rank transform is a nonlinear filter that highly compresses the signal dynamics. From the  $2^{32}$  levels of a float signal, the rank gives a signal of  $d^2 - 1$  levels where  $d$  is the rank filter window diameter. By this compression effect on the signals’ gradient, the rank filter enhances the robustness of the motion estimation and offers the ability to compute the motion between relatively different SAR images such as an SL and an SM SAR image (see Fig. 5).

The second modification of eFolk concerns the variation of the size of the windows  $\omega$  in a coarse to fine fashion during the iterative part at each level of the multiscale solving. This modification lies in the fact that the multiscale pyramid used is a dyadic pyramid, and in large motion, we have to smooth the descent step between different scales in order to have good convergence.

Hence, there are essentially four parameters that need to be adapted to the case of SAR images:

- weighting function  $w$ ;
- choice of the window’s radius  $r$ ;
- $K$ , the number of iterations per level;
- $J$ , the number of pyramid levels.

### B. Adaptations of Parameters for SAR Coregistration

One way to assess the performance of the coregistration is to use a criterion called a forward–backward criterion [8]. It involves computing a displacement between image 1 and image 2 then between image 2 to image 1 and calculating the residual displacement called forward–backward flow. This resulting combined displacement should be theoretically zero. Therefore, this forward–backward error is a good indicator of the performance of the displacement estimate, even without ground truth.

We have plotted the result error distribution for two registration cases of two TerraSAR-X images of San Francisco in Fig. 1. In the first case, two images of different modes, SM and

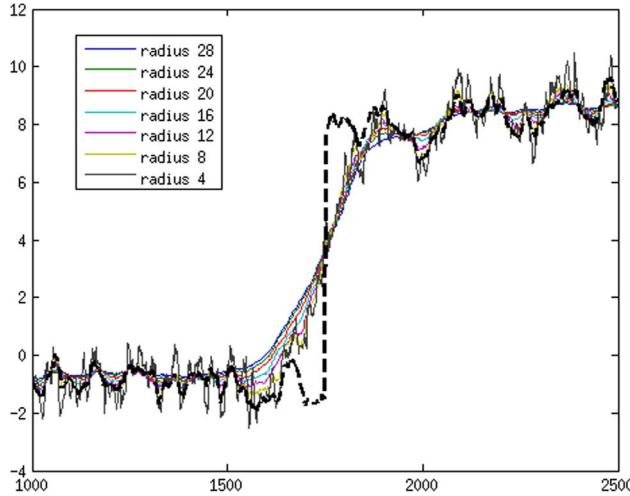


Fig. 2. Norm of the optical-flow between SL and an artificially shifted SM. (Black dashed line) motion without artificial shift and radius 8.

SL, with high temporal decorrelation, have been coregistered. The mean error was estimated at 0.1 pixel. In the second case, two SL images have been coregistered, and the mean error was estimated at 0.07 pixel. These images will be further analyzed in Section III-B.

This criterion can be used to determine the window radius  $r$  most suitable. Tests have shown that the higher the window radius is, the better the result. This can be against-intuitive but is actually mainly because, when the window is wider, the estimated motion is smoother, as illustrated in Fig. 2. In this figure, displacement profiles were calculated for several radius to coregister our pair of images, on which a 9-pixel shift was artificially added 9 on one of our images from the pixel number 1750. Generally, in cases of SAR images where the displacement we are looking for is simple enough, finding the smoothest possible spatial function is an advantage. Then, estimating the displacement in both directions, from 1 to 2 and from 2 to 1, becomes beneficial for the criterion. It could be that these trends are also due to the fact that we are less sensible to speckle effects using large windows.

The same tests were undertaken for the number of iterations. Again, the result is different from that in the optical case: Best results are obtained for a small number of iterations. The more we iterate, the more the function  $u$  tries to fit the data and find details at high frequencies, which is not good our final criterion.

### III. APPLICATIONS AND PERFORMANCE EVALUATION

Now that we have presented the general principles of the method, we propose applying it to SAR images as a preliminary step to two key radar applications, i.e., change detection and interferometry. For each of these applications, results of the coregistration method are presented, as well as its advantages in the specific framework.

#### A. Change Detection

Change detection is a major application in remote sensing. It aims at detecting areas of an image that have changed between two given dates. In this context, the radar provides very robust performance because the image obtained is independent

of illumination conditions. The most relevant configuration is when the available data are of the same type from the same sensor with the same parameters (i.e., incidence, resolution, and frequency). However, obtaining such data is not always possible in the short term if the revisit time of a single sensor is too large or if their characteristics (incidence) during its passage are not close enough. In particular, the current situation tends to favor the use of images from different sources (TerraSAR-X, CSK, RADARSAT, etc.). In this context, we have already demonstrated in [9] the feasibility of change detection between images of different resolutions or either in interferometric conditions or in noninterferometric conditions.

The first case will be discussed in the next section. The second case is illustrated on images of Toulouse taken by the airborne system RAMSES of ONERA. The data to compare are a high-resolution SAR image (SM mode with a resolution of  $10\text{ cm} \times 20\text{ cm}$  in an HH polarization) acquired in 2004 and a polarimetric SAR image (SM mode with a resolution of  $60\text{ cm} \times 60\text{ cm}$ ) acquired in 2005.

The coregistration is the first preprocessing step that aims to compute the images on a common spatial grid. As images are not in interferometric conditions, a variable bias of coregistration exists all over the image because the site has a certain relief not constant over the image.

In addition, a classic coregistration supposedly made on flat ground may be insufficient. In addition, methods that exploit the phase difference between the images do not apply here because the images are not in interferometric conditions.

To overcome this issue, a nonrigid deformation has been searched to be capable of locally warping the slave image to align with the master image of lowest resolution due to eFolki.

Then, change detection algorithm has been successfully applied on the coregistered images [9]. Several parts of the image show the interest of such a sufficiently precise coregistration of the entire image, which compensates for the effects of reliefs, for change detection. We show some examples in Fig. 3, where several extracts are zoomed in order to compare visualization results between a classical rigid coregistration and the nonrigid eFolki method.

For example, on the first zoom over a roundabout, fixed targets are split as circles in red, which can lead to a false detection. When coregistration is performed using eFolki, the fixed targets overlap well. Actual changes appear better by contrast. In the second example on the top right of the image, the construction of a building is shown in yellow. When the coregistration is not sufficiently precise, the strong double-bounce lines of buildings present in both images are badly superimposed as circled in red. When the coregistration is made by eFolki, the double-bounce lines present in both images do not lead to false detections.

Coregistration accuracy over a wide and high-resolution image with a potential relief can be useful when considering applications such as counting vehicles on parking as in the last extract. Vehicles that have disappeared appear in blue, whereas vehicles that appeared between the dates of acquisition appear in yellow.

#### B. Interferometry

Most SAR applications make use of the amplitude of the return signal and ignore the phase data. However, interferometry uses

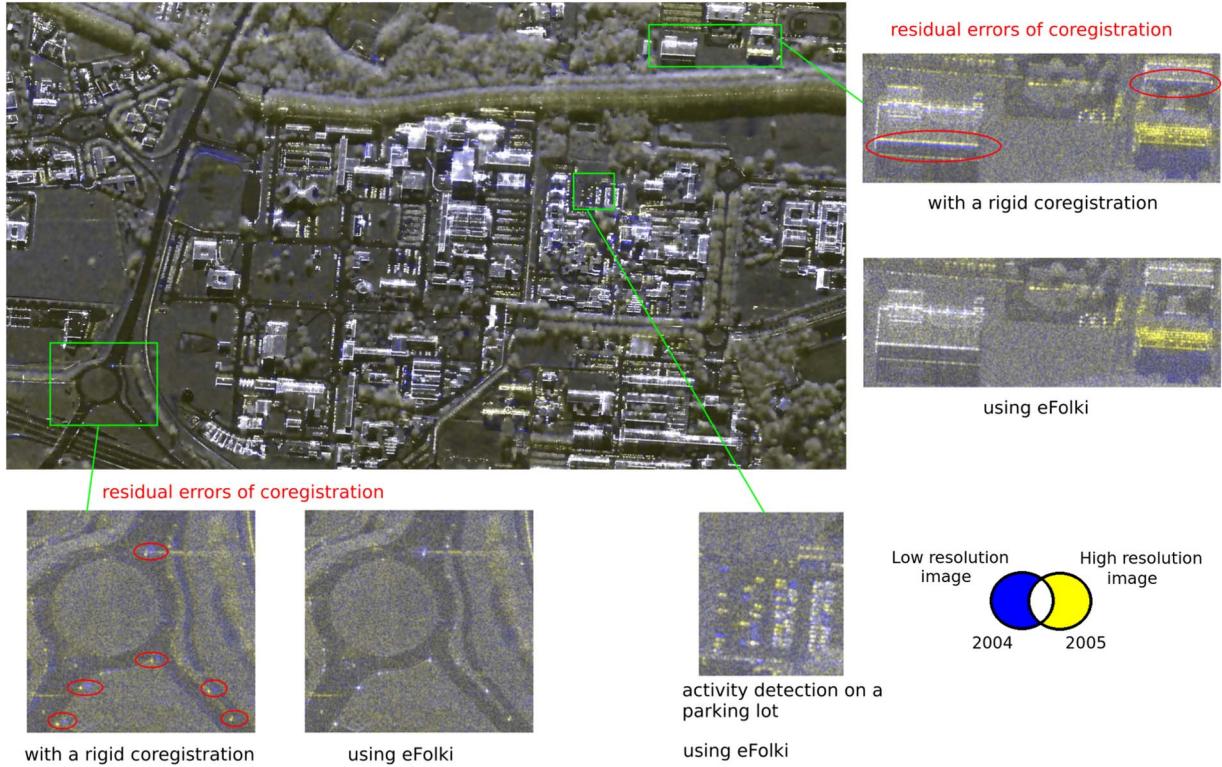


Fig. 3. Superposition of both images. (Yellow) High-resolution image (2005). (Blue) Low-resolution image (2004). Some extracts are shown and compared between a superposition performed using a classical rigid coregistration of 1-pixel precision and a superposition performed using eFolk.

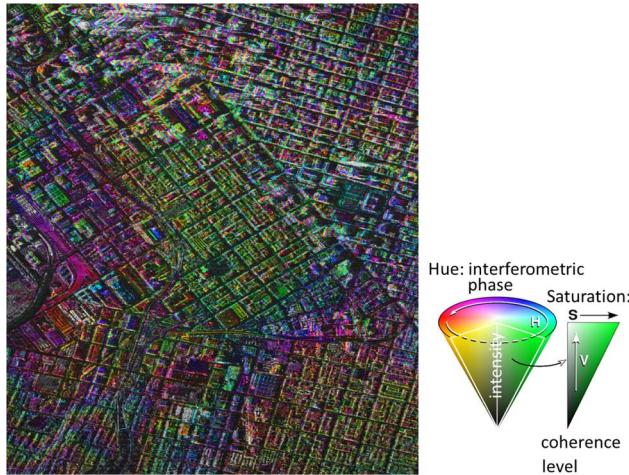


Fig. 4. Interferograms obtained after coregistration by eFolk, between two SL images with an 11-day temporal baseline.

the phase of the reflected radiation. The phase difference between two coregistered images is proportional to the elevation of the target and also to its radial velocity if the target has moved. To obtain a valuable measure of phase, it is therefore essential to coregister the two images with accuracy values on the order of a tenth of a pixel or less.

eFolk has been applied to various images under interferometric conditions. For example, the image in Fig. 4 is the resulting interferogram obtained by combining two SL high-resolution images with an 11-day revisit time. eFolk has been also proven to be effective for images with a long temporal baseline at X-band in a situation of high temporal decorrelation. A special effort has been focused on the coregistration of

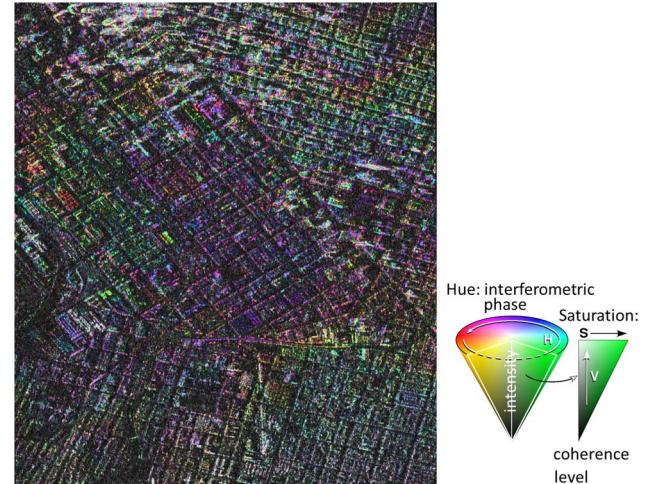


Fig. 5. Interferograms obtained after coregistration by eFolk, between an SL image and an SM mode image, using two different resolutions and radar modes with an 18-month temporal baseline.

data with different resolutions. In Fig. 5, two images with two different resolutions and a revisit time of 18 months are combined.

Here, the contribution of eFolk is twofold.

- It manages to coregister interferometric data in difficult configurations, with levels of low-coherence interferometry (0.3 average after coregistration for coherence calculated with a  $5 \times 5$  window).
- eFolk does not use the relative phases of the signal or external data such as orbits or DEM.

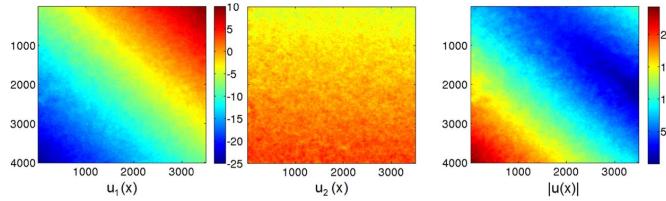


Fig. 6. Maps of flow estimation over the interferometric pair of different resolutions (SM-SL modes).

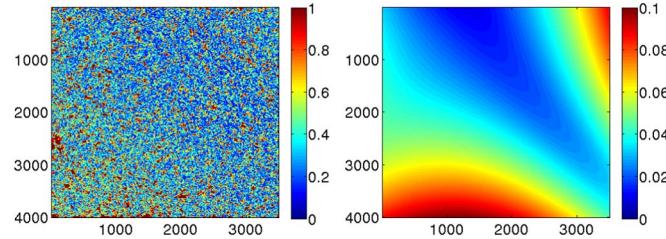


Fig. 7. Maps of error estimation: (left) without polynomial regression and (right) after polynomial regression on the flows.

In order to further assess the quality of the coregistration, we have represented the flow estimated on this last image pair, represented in Fig. 6. The variation of the flow all over the image can reach more than 20 pixels. If we compute the forward–backward flow error, we obtain the distributions already shown in Fig. 1, with a 0.1-pixel mean error, and the spatial distribution is given on the left image in Fig. 7. If a polynomial regression is applied to the estimations of the flows before the forward–backward flow error estimation, then the result is shown on the right. The mean value lies around 0.02 pixel and never exceeds 0.1 pixel. This confirms that even in a challenging case, the average error is compatible with the interferometry applications.

#### IV. CONCLUSION

This letter has presented eFolki, an algorithm for evaluating the displacement between two intensity images, without external data. By adapting the eFolki parameters such as the size of the search window and the scale level for radar images, subject to speckle noise, the result is conclusive for coregistration of high-resolution urban SAR images.

- The robustness makes the registration method efficient under all conditions encountered: change detection under noninterferometric conditions and relief effect and interferometry using different resolutions.
- The accuracy of the estimated determined offset is on the order of one-tenth of the pixel in the most difficult configurations.

Although the estimation of the movement is made for all the pixels, the execution time remains acceptable on the order of 1 min in MATLAB on our 4000 pixel  $\times$  4000 pixel image.

This initiated work opens the door to many opportunities, including the application for registration algorithms in more complex situations and the feasibility of the joint registration and intended application, for example, change detection. Future work will concern the evaluation of the limit of eFolki registration for various SAR configurations, by comparing results with reference algorithms, and will also consider its use for multi-sensor configurations. We will therefore keep in mind the main limitation of the algorithm: In case of strong discontinuities in the flow, such as for buildings seen and different headings, the algorithm will tend to smooth the result.

#### ACKNOWLEDGMENT

The authors would like to thank H. Cantalloube of ONERA for the processing of RAMSES PolInSAR images, the Direction Générale de l'Armement (DGA), and the Centre National d'Études Spatiales (CNES) for their support to the acquisition campaign with the ONERA RAMSES airborne system. They would also like to thank M. Foumelis of ESA-ESRIN for his very informative recommendations. SM TerraSAR-X images have been obtained through the ESA POLSARAP project thanks to I. Hajnsek of the German Aerospace Center (DLR). Spotlight TerraSAR-X images have been obtained through the 2012 Data Fusion Contest for which the authors thank the Technical Committee.

#### REFERENCES

- [1] Z. Li and J. Bethel, "Image coregistration in SAR interferometry," in *Proc. Int. Arch. Photogramm., Remote Sens. Spatial Inf. Sci.*, 2008, pp. 433–438.
- [2] G. Fornaro, M. Manunta, F. Serafino, P. Berardino, and E. Sansosti, "Advances in multipass SAR image registration," in *Proc. IEEE IGARSS*, Jul. 2005, vol. 7, pp. 4832–4835.
- [3] L. Liu, Y. Wang, and Y. Wang, "Sift based automatic tie-point extraction for multitemporal SAR images," in *Proc. IEEE Int. Workshop ETT GRS*, Dec. 2008, vol. 1, pp. 499–503.
- [4] B. D. Lucas and T. Kanade, "An iterative image registration technique with an application to stereo vision," in *Proc. IJCAI*, 1981, vol. 81, pp. 674–679.
- [5] A. Plyer, G. Le Besnerais, and F. Champagnat, "Massively parallel Lucas Kanade optical flow for real-time video processing applications," *J. Real-Time Image Process.*, pp. 1–18, Apr. 2014.
- [6] G. Le Besnerais and F. Champagnat, "Dense optical flow by iterative local window registration," in *Proc. IEEE ICIP*, 2005, vol. 1, pp. 137–140.
- [7] F. Champagnat *et al.*, "Fast and accurate PIV computation using highly parallel iterative correlation maximization," *Exp. Fluids*, vol. 50, no. 4, pp. 1169–1182, Apr. 2011.
- [8] P. Sand and S. Teller, "Particle video: Long-range motion estimation using point trajectories," *Int. J. Comput. Vision*, vol. 80, no. 1, pp. 72–91, Oct. 2008.
- [9] F. Weissgerber, E. Colin-Koeniguer, and F. Janez, "Urban change detection by comparing SAR images at different resolutions and polarimetric modes," in *Proc. IEEE 10th EUSAR 2014*, Berlin, Germany, Jun. 2014, pp. 1–4.