Analysis of the Effects of Registration Noise in Multitemporal VHR Images

Francesca Bovolo, Member, IEEE, Lorenzo Bruzzone, Senior Member, IEEE and Silvia Marchesi, Student Member, IEEE

Abstract—This paper analyzes the problem of change detection in very high resolution (VHR) multitemporal images by studying the effects of residual misregistration (registration noise) between images acquired on the same geographical area at different times. In particular, according to an experimental analysis driven from a theoretical study, the main effects of registration noise on VHR images are identified and some important properties are derived and described in a change vector polar framework. In addition, a technique for an adaptive and unsupervised estimation of the registration noise distribution in the polar domain is proposed. This technique derives the conditional distribution of registration noise according to a multiscale analysis of the distribution of spectral change vectors. Experimental results obtained on simulated and real images confirm the validity of the proposed analysis, the reliability of the derived properties and the effectiveness of the proposed estimation technique. This technique represents a very promising tool for the definition of change-detection methods for VHR multitemporal images robust to registration noise.

Index Terms—Change detection, change vector analysis, registration noise, very high resolution images.

I. INTRODUCTION

The availability of remote sensing images regularly acquired by satellites over the same geographical area makes the analysis of multitemporal data (and the related applications) one of the most interesting research topics for the remote sensing community. In particular, multitemporal images represent a valuable information source for performing the detection of changes occurred on the Earth surface at different scales. Change-detection techniques generally compare two multitemporal images acquired at different times by assuming that they are similar to each other except for the presence of changes occurred on the ground. Unfortunately, this assumption is seldom completely satisfied due to differences in atmospheric and sunlight conditions, as well as in the sensor acquisition geometry. In order to satisfy the similarity assumption, pre-processing steps are required, including: image co-registration, radiometric and geometric corrections, and noise reduction. Among the others, co-registration plays a fundamental role as it allows one to obtain a pair of images where corresponding pixels are associated with the same position on the ground. However, in practice, it is not possible to obtain a perfect alignment between images acquired at different times. This may significantly affect the accuracy of the change-detection process. The co-registration procedure becomes more complex and critical (and therefore intrinsically less accurate) when very high resolution (VHR) images acquired by the last generation sensors (e.g. Ikonos, Eros, Quickbird, Pleiades, SPOT-5) are considered. These images can be acquired with different view angles and often show different geometrical distortions that, even after proper geometric corrections, strongly affect the precision of the registration process, resulting in a significant residual registration noise (RN). This noise sharply decreases the accuracy of the change-detection process.

In the literature special attention has been given to the development of advanced registration techniques, especially for what concerns medium resolution multitemporal and multisensor images [1]-[5]. In addition some studies exist on the effects of misregistration on the change detection accuracy [6]-[12]. Nonetheless, in our knowledge no studies are reported on the effects and the properties of registration noise in VHR images.

This work aims at analyzing the behavior and the effects of registration noise in multitemporal VHR images in order to define the basis for the development of novel change-detection techniques robust to registration noise. The current study is developed within a polar framework for change vector analysis (CVA) recently introduced in the literature for change detection in medium resolution multispectral images [13]. The definition of this framework is based on the analysis of the distribution of spectral change vectors (SCVs) computed according to the CVA technique in the polar domain. In this context the novel contributions of this work consist in: i) the analysis of the effects of registration noise in multitemporal and multispectral VHR images according to the study of the statistical distribution of SCVs in the polar domain; ii) a formal definition of the properties of registration noise in VHR images in the polar domain; and iii) the formulation of an adaptive and unsupervised technique for the estimation of the distribution of the registration noise in the polar domain. This last technique takes advantage from both a multiscale decomposition of multitemporal images and the properties derived in the first part of this work. The experiments carried out on simulated and real multitemporal Quickbird images confirm the validity of the theoretical analysis and the effectiveness of the proposed technique, which represents a valuable tool for the development of valid change-detection techniques for multitemporal and
multispectral VHR images.

The paper is organized into six sections. The next section briefly recalls the notation and the background of the polar framework proposed in [13]. Section III describes the experimental setup for the study of the properties of registration noise on simulated multitemporal VHR images. Section IV derives and defines the properties of registration noise. Section V illustrates the proposed approach to the estimation of the distribution of registration noise in the polar domain. The validation on real multitemporal Quickbird images of both the derived properties and the proposed technique for the estimation of the registration noise is presented in section V, where a simple example of the advantages that the proposed estimation technique can introduce in the change-detection process is also given. Finally, section VI draws the conclusions of this work.

II. NOTATION AND BACKGROUND

In order to analyze the effects of the registration noise, we take advantage from the theoretical polar framework for unsupervised change detection based on change vector analysis (CVA) proposed in [13]. Therefore in the following we briefly recall the main concepts of this framework. The reader is referred to [13] for greater details.

Let us consider two VHR multispectral images $X_1$ and $X_2$ (e.g. Ikonos, Eros, Quickbird, Pleiades, SPOT-5 images) acquired over the same geographical area at different times $t_1$ and $t_2$, respectively. Let us assume that these images do not show significant radiometric differences and that present a residual misregistration after the co-registration procedure. Let $\Omega=\{\omega_0,\Omega_c\}$ be the set of classes of changed and unchanged pixels to be identified. In greater detail $\omega_0$ represents the class of unchanged pixels and $\Omega_c=\{\omega_1,...,\omega_K\}$ the set of the $K$ possible classes (kinds) of changes occurred in the considered area. For simplicity, as in [13], the whole analysis on the registration noise is carried out considering a 2-dimensional feature space (however it can be generalized to the case of more dimensions). Let $X_0$ be the multispectral difference image computed according to the CVA technique by subtracting the spectral feature vectors associated with each corresponding spatial position in the two considered images. $X_0$ is a multidimensional image made up of spectral change vectors (SCVs) defined as:

$$X_0 = X_2 - X_1$$

The change information contained in the SCVs can be univocally described by the change vector magnitude $\rho$ and the change vector direction $\vartheta$ defined as:

$$\vartheta = \tan^{-1}\left(\frac{X_{1,0}}{X_{2,0}}\right) \quad \text{and} \quad \rho = \sqrt{(X_{1,0})^2 + (X_{2,0})^2}$$

where $X_{b,0}$ is the random variable representing the $b$-th component (spectral channel) of $X_0$ ($b=\{1,2\}$). Finally, let us define the magnitude-direction domain $MD$ (in which all the SCVs of a given scene are included) as:

$$MD = \{\rho \in [0, \rho_{\text{max}}] \text{ and } \vartheta \in [0, 2\pi]\}$$

where $\rho_{\text{max}} = \max\left\{\sqrt{(X_{1,0})^2 + (X_{2,0})^2}\right\}$. From the theoretical analysis reported in [13] and under the above-mentioned assumptions, it is expected that in the polar representation unchanged and changed SCVs result in separated clusters. Unchanged SCVs show a low magnitude and are uniformly distributed with respect to the direction variable. In the polar domain the region associated with them is the circle of no-changed pixels $C_n$ defined as:

$$C_n = \{\rho, \vartheta : \rho < \rho_{\text{max}} \text{ and } 0 \leq \vartheta < 2\pi\}$$

This circle is centered at the origin and has a radius equal to the optimal (in the sense of the theoretical Bayesian decision theory) threshold $T$ that separates unchanged from changed pixels. On the opposite, changed SCVs are expected to show a high magnitude. The region associated with them in the polar domain is the annulus of changed pixels $A_c$, defined as:

$$A_c = \{\rho, \vartheta : T \leq \rho \leq \rho_{\text{max}} \text{ and } 0 \leq \vartheta < 2\pi\}$$

This annulus has inner radius $T$ and outer radius given by the maximum among all possible magnitudes for the considered pair of images ($\rho_{\text{max}}$). As unchanged SCVs show preferred directions according to the kind of change occurred on the ground, different kinds of changes can be isolated with a pair of threshold values $(\vartheta_{\text{L}}, \vartheta_{\text{H}})$ in the direction domain. Each pair of thresholds identifies, in the annulus of changed pixels $A_c$, an annular sector $S_k$ of change $\omega_k \in \Omega_c$, defined as:

$$S_k = \{\rho, \vartheta : \rho \geq T \text{ and } \vartheta_{\text{L}} \leq \vartheta \leq \vartheta_{\text{H}}, 0 \leq \vartheta < 2\pi\}$$

All the mentioned regions are depicted in Fig. 1. The reader is referred to [13] for further details on both the polar framework and the properties of SCVs in this kind of representation.

III. DEFINITION OF THE ANALYSIS AND EXPERIMENTAL SETUP

The objective of this work is to study the effects of misregistration within the framework presented in Sec. II in order to derive its properties and to define a procedure for an adaptive estimation of the distribution of registration noise. The residual registration noise can be modeled as the effect of different types of transformations between the images, such as scale, rotation, translation and skew. In this work we assume that the residual registration noise can be modeled only as a translational effect between the two analyzed images. This
simplifying assumption is reasonable as it is expected that in the polar domain non-translational effects will show, from the statistical viewpoint, a behavior similar to that of the translational ones.

In order to analyze the behavior of registration noise in the polar CVA domain several data sets have been selected by considering: i) very high geometrical resolution images acquired by different sensors (i.e., Quickbird, Ikonos, and Pleiades); and ii) areas with different characteristics, representative of the most important land cover types (i.e., urban, rural and forestry). In order to understand the behavior of RN on: (1) unchanged pixels; (2) changed pixels; and (3) both unchanged and changed pixels at different resolution levels, three experiments have been defined. In order to avoid intrinsic differences between images typical of real multitemporal data sets (e.g., atmospheric differences, etc.), in the first phase of the analysis a single-date image has been considered for each data set, while the second acquisition has been simulated. The analysis carried out on the single-date data sets will be extended to real multitemporal images in section VI.

In the following we describe the experiments considering the analysis conducted on a Quickbird image acquired on the city of Trento (Italy) in July 2005 ($X_1$). The selected test site is a section of a full scene including both rural and urban areas (Fig. 2 (a)). Results obtained on the other data sets are very similar to those reported, and omitted for space constraints.

A. Experiment 1: Effects of increasing misregistration on unchanged pixels

From the considered image $X_1$ different simulated images $X_2$ have been generated introducing some pixels of misregistration according to: translations in several directions; this resulted in different multitemporal data sets made up of the original image $X_1$ and of its shifted versions $X_2$. In particular, we considered misregistration between 1 and 6 pixels, which are reasonable values when taking into account VHR images acquired with different view angle and/or in complex areas.

CVA has been performed involving the red and near infrared spectral channels of the considered data sets, and the SCV distributions were analyzed in the polar scatterograms in order to derive the properties of RN on unchanged pixels (see Sec. IV.A). It is worth nothing that the application of the CVA technique to $X_1$ and a copy of itself when images are perfectly co-registered leads to a multispectral difference image made up of SCVs with all zero components. Thus the representation in polar coordinates of SCVs collapses in a single point at the origin. This is no longer valid if CVA is applied to misregistered images; in this case the distribution of SCVs in the polar domain corresponds to the distribution of registration noise (as no changes are present in the considered data set). Fig. 3 (a) and (b) show an example of the behaviors of scatterograms obtained after applying CVA to $X_1$ and its 2- and 6-pixels shifted versions, respectively. An analysis of these scatterograms allows us to derive the properties of registration noise in images when no changes are present in the data set (see Sec. IV.A).

B. Experiment 2: Effects of increasing misregistration on changed pixels

From the considered image $X_1$ a new image $X_2$ is generated by adding simulated changes. These changes have been
accurately introduced in order to be as similar as possible to real changes. In particular, some buildings have been added to the scene (see regions marked with white circles in Fig. 2 (a)) taking their geometrical structures and spectral signature from other real buildings present in the image. All the mentioned buildings have similar spectral signatures and are located on agricultural fields. Therefore the solution of the simulated change-detection problem requires the identification of a single class \( c_\omega \) of changed pixels. From the simulated image, as in the first experiment, 6 new images are generated introducing some pixels of residual misregistration. This results in seven multitemporal data sets made up of the original image \( X_1 \) and one of the simulated images \( X_2 \). In particular, the two images in the first data set are perfectly aligned and differ only for the simulated change, while the images in the others data set show also from 1 to 6 pixels of residual misregistration.

It is worth noting that the application of the CVA technique to \( X_1 \) and to the image obtained introducing simulated changes when the images are perfectly co-registered leads to a multispectral difference image made up of SCVs with non-zero values associated only to the simulated changes. Other non-zero SCVs appear if we compute the scatterograms considering the misregistered image pairs. Fig. 4 shows an example of the behaviors of such scatterograms obtained after applying the CVA technique to the image \( X_1 \) and: (a) the simulated image perfectly aligned; (b) the simulated image with 2 pixels of residual misregistration; and (c) the simulated image with 6 pixels of residual misregistration. The red and the near infrared spectral channels have been considered. An analysis of these scatterograms (and of the others obtained for different values of misregistration) allowed us to derive the properties of the registration noise on the class of changed pixels (see Sec. IV.B).

C. Experiment 3: Effects of misregistration at different resolution levels.

Further data sets have been generated from the considered image \( X_1 \) and the simulated image with a 4-pixel misregistration \( X_2 \) by applying to them the Daubechies-4 stationary wavelet transform [15], [16], independently. Two sets of images \( X_1^n \) and \( X_2^n \), \( n=1,2,...,N \) were generated that have lower resolution than the original one. In the following, as an example, the results achieved considering the couple of images obtained by the third decomposition level \( n=3 \) are reported. Fig. 5 (a) and (b) reports the scatterograms obtained after applying the CVA technique to the red and infrared spectral channels of images \( X_1 \) and \( X_2 \) (full resolution) and to \( X_1^n \) and \( X_2^n \), respectively. By comparing these scatterograms (and the others obtained for different values of misregistration) allowed us to derive the properties of the registration noise on both unchanged and changed pixels.

IV. PROPERTIES OF REGISTRATION NOISE IN VHR IMAGES

An analysis of the scatterograms obtained from the three sets of previous described experiments and a deeper study on the behavior of SCVs in the polar domain for each investigation setting allowed us to derive some important properties of the registration noise on both unchanged and changed pixels.

A. Effects of registration noise on unchanged pixels

Experiment 1 makes it possible the study of the behavior of the distribution of registration noise (associated with the distribution of SCVs) versus different amounts of misregistration in the polar domain. Two different contributions to the distribution of the SCVs in the polar domain can be identified: i) the first one is related to the comparison of pixels that belong to the same object in the two images, but that are not associated to the same position on the
ground due to misregistration; ii) the second one comes from the comparison between pixels that belong to different objects in the two images (pixels associated with details and border regions). Each contribution results in a specific property of the registration noise. A third important property is derived from the results of experiment 3, and derives from the analysis of the behaviors of SCVs associated to registration noise and related to unchanged areas when varying the considered resolution (scale) level.

**Property 1.** The variance of the cluster of unchanged pixels increases when residual misregistration increases.

Observing the scatterograms of Fig. 3, it is possible to note that some SCVs associated with unchanged pixels that should usually stay in $C_o$, fall in $A_c$. Nevertheless they still show a relative low magnitude and a uniform distribution along the direction variable, as it happens for medium resolution images [13] (see regions marked with the continue line circle in Fig. 3). This effect is generated by the fact that increasing the registration noise the spread of the cluster of unchanged pixels increases due to the comparison of pixels belonging to the same object but not associated to the same area on the ground. With respect to medium resolution images, in VHR images the spread of SCVs associated with unchanged pixels is sharply amplified due to the higher spectral heterogeneity within the objects. It is worth noting that the rather uniform distribution of SCVs along the direction is due to the fact that the structure of details inside each object is usually different for different elements in the scene.

A quantitative analysis of the variance of the cluster of unchanged patterns versus the amount of misregistration (in pixels) carried out separately on each of the four bands of the considered difference image (Fig. 6) points out that it increases in a non-linear way by increasing the misalignment. In particular, when the residual registration noise is over a given threshold the variance saturates.

According to this property we expect that the threshold $T$ which separates $C_o$ from $A_c$ (see Sec. II), is higher than in the case of perfect alignment between the images and its value increases as registration noise does.

**Property 2.** By increasing the registration noise unchanged pixels generate clusters with properties very similar to clusters of changed pixels.

Observing scatterograms in Fig. 3, it is possible to note that a large number of unchanged SCVs show a significantly higher magnitude than expected and fall therefore far from the origin in $A_c$ (see regions marked with dashed circles in Fig. 3). As for medium resolution images, these are SCVs rising from the comparison of unchanged pixels associated with different objects on the ground due to misregistration. In the medium resolution case the distribution of such SCVs is nearly uniform along the direction [13]. On the contrary when dealing with VHR images their distribution assume preferential directions, involving the detection of significant clusters of pixels of registration noise in $A_c$, showing properties very similar to the ones of changed pixels. This effect is mainly due to the regular structure of the urban areas and of the crop rows, as well as to the high frequency content of the VHR images. Annular sectors in the polar domain associated to these clusters can be defined similarly to what done for changed pixels [see (6)]. In greater detail, the sector of dominant registration noise $S_{RN}^D$ is defined as:

$$S_{RN}^D = \{ \rho, \vartheta : \rho \geq T \text{ and } \vartheta_1 \leq \vartheta \leq \vartheta_2, 0 \leq \vartheta_1 < \vartheta_2 < 2\pi \} \quad (7)$$

Each $S_{RN}^D$ can be represented in the polar domain as a sector within the annulus of changed pixels bounded from two angular thresholds $\vartheta_1$ and $\vartheta_2$. This is not surprising as SCVs of dominant misregistration, exactly as SCVs of true changes, originate from the comparison of pixels that belong at the two acquisition dates to different objects (or natural classes) on the ground. Therefore SCVs generated from the comparison of the same pair of different spectral signatures (e.g., in the considered data set pixels that belong to buildings at $t_1$ and to crop fields at $t_2$) fall in the same sector independently on whether they are associated with misregistered or changed pixels. It follows that sectors of dominant registration noise are very critical because they cannot be distinguished from sectors of true changes at full resolution, resulting in a significant false alarm rate in the change-detection process.

**Property 3.** The effects of registration noise on unchanged pixels are not stationary with respect to the resolution (scale) of the images.

Comparing the scatterograms of Fig. 5 (derived from experiment 3) it can be observed that reducing the resolution, SCVs associated with registration noise tend to disappear. This is because they are usually generated from small and thin structures, which are smoothed out from the low-pass effects associated with scale (resolution) reduction. In other words, decreasing the resolution level sectors of dominant registration noise tend to disappear showing a non stationary behavior with respect to scale. In particular, such SCVs tend to collapse within the circle of unchanged pixels in the polar domain. This is confirmed from an analysis on how the mean value of the magnitude of SCVs associated to RN noise varies. As can be seen from dashed line in Fig. 7 their mean value rapidly decreases with the resolution. This property is very important in the definition of a strategy for estimating the distribution of RN in VHR images (see Sec. V).

**B. Effects of registration noise on changed pixels**
Experiment 2 makes it possible to identify the behaviors of SCVs related to changed pixels in the polar domain versus the amount of registration noise that affects the considered simulated data sets. Indeed, from experiment 3 we can observe the effects of a multiscale decomposition of the images on pixels of registration noise associated with real changes.

**Property 4.** Clusters associated with changed pixels are nearby stationary versus the amount of misregistration between images.

By observing Fig. 4 it is possible to note that SCVs associated with the class of changed pixels $\omega_{c1}$ are not significantly affected by an increase of the amount of misregistration between images. Indeed, the cluster of changed pixels can be easily identified in all the three scatterograms and shows quite stable behaviors (see regions marked with circles in Fig. 4). The position of sector $S_1$ that identifies pixels belonging to $\omega_{c1}$ is almost invariant with the resolution. This behavior allows one to conclude that the registration noise does not affect significantly the properties of the cluster of changed pixels. Nonetheless, the RN affects the detection of changed pixels as: (i) the increase of variance of the patterns in the circle of unchanged pixels increases the overlapping between cluster of changed and unchanged pixels; (ii) the presence of sectors of dominant RN in the annulus of changed pixels results in false alarms.

**Property 5.** Clusters associated with changed pixels have nearby stationary statistical properties with respect to the resolution (scale) of the images.

Observing regions marked with circles in Fig. 5 it is possible to note that the cluster of pixels associated with true changes reduces its spread, but is not completely smoothed out when the resolution decreases. In other words, it shows a stationary behavior versus the resolution. This is confirmed by an analysis of the behaviors of the mean value of the magnitude of SCVs associated with true changes versus the scale. As can be seen from the continuous line in Fig. 7, the mean value slightly varies with the resolution, but it decreases slower than the one of SCVs associated with registration noise (dashed line in Fig. 7). It follows that the behaviors of changed and unchanged (i.e., the ones due to RN) SCVs that fall in $A_c$ are different (i.e. one the opposite of the other) versus the resolution (see property 3): decreasing the resolution, sectors of changes, unlike sectors of dominant registration noise, are preserved. It is important to note that one of the main assumptions at the basis of this analysis is that, given the very high geometrical resolution of images, we implicitly decrease the impact of the registration noise with respect to that of the original scene (Property 3), while true changes maintain a certain stability (Property 5). In other words, the lower is the geometrical resolution; the lower is the probability of identifying in the polar representation annular sectors of dominant registration noise. This means that at low resolution in the *annulus of changed pixels* mainly sectors (i.e., clusters) due to the presence of true changes on the ground can be detected. However, in order to obtain a change-detection map characterized by a good geometrical fidelity, we should work at full resolution by properly integrating the use of the statistical distribution of RN in the decision strategy.

On the basis of these considerations, we propose a multiscale context-sensitive strategy that exploits the behaviors of SCVs in the polar domain in order to identify the distribution of the registration noise. In the proposed technique, first of all the two multitemporal images are decomposed according to a multiscale transformation (different algorithms can be used, like gaussian pyramid decomposition, wavelet transform, recursively upsampled bicubic filter, etc.), obtaining two sets of images $X_{MS} = \{X_0^o, ..., X_{N-1}^o\}$ where the subscript $i (i = 1, 2)$ denotes the acquisition date, and the superscript $n (n = 0, 1, ..., N-1)$ indicates the resolution level, $X_n^o \equiv X_n^c$. Then the CVA technique is applied to each corresponding pair of images.
(X\textsubscript{1}\textsuperscript{c}, X\textsubscript{2}\textsuperscript{c}) and the distributions of the direction of SCVs at different resolution levels are analyzed. In particular, the behavior of SCVs in the A\textsubscript{c} are studied. For this purpose we estimate the marginal conditional density of the direction of pixels in A\textsubscript{c} and we observe its behaviors versus the scale. According to the properties of RN, this density decreases at reduced resolutions in the annular sectors of dominant registration noise S\textsubscript{DRN} (hencewhere indicated as S\textsubscript{DRN}). On the basis of this consideration, we estimate the conditional density of dominant registration noise (DRN) in the direction domain as:

$$\hat{P}(\vartheta | \rho \geq T) = C[P(\rho \geq T)\hat{p}(\vartheta | \rho \geq T) - P^{N-1}(\rho \geq T)p^{N-1}(\vartheta | \rho \geq T)]$$

where $P(\rho \geq T)$ and $P^{N-1}(\rho \geq T)p^{N-1}(\vartheta | \rho \geq T)$ are the marginal conditional densities of the direction of pixels in A\textsubscript{c} at the full resolution and at the lowest considered resolution level, respectively; T is the threshold value that separates the circle of unchanged pixels from the annulus of changed pixels and C is a constant defined such that:

$$\int_{-\infty}^{\infty} \hat{p}(\vartheta | \rho \geq T) = 1.$$ 

In this way we obtain an estimation of the distribution of registration noise that is adaptive (in the sense that it intrinsically takes into account the properties of the considered images) and that can be used in the decision strategy of any change detection technique.

VI. EXPERIMENTAL RESULTS

In this section an example of application of the proposed method to estimate the distribution of registration noise on real multitemporal images is reported. In the experiments a real multitemporal data set made up of Quickbird images acquired on the Trento city (Italy) in July 2006 (Fig. 2 (a)) (this is the image described in Sec. II) and in October 2005 (Fig. 2(b)) was used. The final data set is made up of two pansharpened multitemporal and multispectral images of 984 x 984 pixels with a spatial resolution of 0.7 m, which have a residual misregistration of about 1 pixel on ground control points.

Between the two acquisition dates, as mentioned above, two kinds of changes occurred: i) a simulated change (see Sec. III.B on how changes have been simulated) which consists of a real houses introduced on rural area (continuous circles in Fig. 2 (a)); ii) a real change which consists of some roofs rebuilt in the industrial and urban area (dashed circles in Fig. 2 (a)). Fig. 8 shows the scatterograms in polar coordinates obtained after applying the polar CVA technique to the red and near infrared spectral channel to: (a) the original images; and (b) a degraded version of them (computed applying a four-step stationary wavelet transform [15],[18] to images X\textsubscript{1} and X\textsubscript{2} using 4th order orthogonal filters of the Daubechies family). A visual analysis of these scatterograms confirms the properties derived from the simulated data sets. Observing the scatterogram at full resolution several (namely 4) different sectors can be identified in the annulus of changed pixels, which are candidate to be sectors of real changes. A comparison between the scatterograms at full and low resolution points out that in two annular sectors the density of the magnitude of SCVs reduces significantly, whereas in others two it is nearly constant. This is confirmed by observing Fig. 9, which shows the behaviors of the marginal conditional densities of the direction in A\textsubscript{c} at resolution level 0 and 4. By using the proposed technique it is possible to derive from the marginal densities at different resolutions an estimation of the marginal conditional density of registration noise (see Fig. 10) according to (8). As expected this distribution confirms that only two of the four identified sectors are associated with real changes, while the others are associated to sectors of registration noise.

Asconst a simple example on the use of the derived distribution, we apply a threshold to the density of RN in order to estimate sector of dominant registration noise. With a threshold in the magnitude domain equal to 220 the sectors of dominant registration noise were identified between 37° and 120°, and 232° and 293°. This information was then used in the context of a standard CVA in the decision procedure by excluding from the group of changed pixels samples included in the sectors of dominant RN. This resulted in a change detection overall error (computed on the basis of the available reference map) of 5967 pixels (see Table I). This error is sharply smaller than the one obtained for comparison with the standard CVA without any analysis of the RN effects (which resulted equal to 195592 pixels). These results point out the effectiveness of the technique for estimating the RN distribution, which provide a very important statistical input to any change-detection algorithm.

VII. CONCLUSION

In this paper we have analyzed the properties of registration noise on very high resolution images (VHR). In particular, the analysis of the behavior of misregistration was carried out in the context of a polar framework for change vector analysis (CVA), where both the magnitude and the direction information of SCVs are represented. On the basis of the derived properties, a novel method for an adaptive estimation of the statistical distribution of registration noise on multitemporal VHR images has been proposed.

Images acquired by several sensors and with different land
different possible strategies.
As future developments of this work we plan to fully exploit the derived properties and the technique for the estimation of the registration noise distribution to develop effective change-detection methods for VHR images based on the Bayesian decision theory.

REFERENCES


TABLE I

<table>
<thead>
<tr>
<th>TECHNIQUE</th>
<th>FALSE ALARMS</th>
<th>MISSED ALARMS</th>
<th>OVERALL ERROR</th>
<th>KAPPA ACCURACY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed method</td>
<td>4213</td>
<td>1754</td>
<td>5967</td>
<td>0.862</td>
</tr>
<tr>
<td>Standard CVA</td>
<td>193820</td>
<td>1772</td>
<td>195592</td>
<td>0.130</td>
</tr>
</tbody>
</table>