Change Detection Methods in High Resolution
Cosmo SkyMed images

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Abstract—In this paper we compare three approaches for
c change detection in SAR imagery: GRLT, MIMOSA and one
based on the Hellinger stochastic distance between distributions.
The comparison is made using COSMO-SkyMed images from
which training samples from four types of areas subjected
to change, and from two areas which underwent no change.
 Whereas GRLT and the Hellinger distance-based procedures
yielded good results, MIMOSA failed at detecting the changes.

I. INTRODUCTION

Research about multi-temporal image analysis has been
expanded because of the increasing availability of data from
Synthetic Aperture Radar (SAR) satellites with characteristics
such as short revisit time, all-day and all-weather acquisitions.
The COSMO-SkyMed (CSK) constellation consist of four
satellites having less than 12 hours revisit time. It represents
a remarkable data source to be used on change detection
applications.

Change detection is based on the comparison of two or
more images from the same scene acquired at different dates,
seeking for change indicators or dissimilarity measures for
each pair of pixels. Classical change detectors can be grouped
in two categories: 1) considering only the pixel intensity of
the images, and 2) considering local statistics in the pixel
neighborhood. Change operators are also divided according
to the number of temporal images employed [1].

Because of the multiplicative nature of speckle in SAR,
which can induce false alarms, classical methods use local
statistics in the neighborhood of each pixel. The standard de-
tector is based on the Log-Ratio [2]–[5] that computes the ratio
of the local means in an image pair. However, if the change
preserves the mean value modifying only the local texture
(modeled as a zero-mean multiplicative contribution [6]), it
will not be detected. The ratio of means would be useful to
recognize step changes whereas higher order statistics would
be suitable to detect progressive changes in multi-temporal
series [5].

Generalized Likelihood Ratio Test (GLRT) [1], [7], Log-
cumulants for spatio-temporal heterogeneity [5], Local statis-
tics Similarity Measures [4] and Information Theoretic ap-
proaches [8], [9] are also applied as change indicators.

In this work, the performance of three different change
detection approaches for CSK images is evaluated. The com-
pared methodologies are: 1) Generalized Likelihood Ratio Test
(GLRT) [1], [7], 2) MIMOSA approach proposed in [10], and
3) Information theory separability measures, e.g. stochastic
distances and their derived hypothesis tests [11]. The assess-
ment considers various change levels: abrupt changes (e.g.
deforestation), evolutionary changes (e.g. vegetation areas), no-
change, i.e., stable areas (e.g. urban regions), and periodic
changes (e.g. vegetation phenology).

II. METHODOLOGY

The data set consists of two CSK-3 images, provided under
the ASI–CONAE SIASGE agreement. The study area is Foz
do Iguazú region, Paraná, Brazil (Fig. 1). The images used
were acquired with identical geometrical characteristics: 29°
incidence angle, right acquisition, descendant orbit, Stripmap
Himage (HI) mode of about 3 m of nominal resolution. The
images were acquired on 2011/04/11 and on 2011/10/20.

The CSK data was preprocessed to obtain intensity cali-
brated data: $\sigma = K^{-1} \sin \alpha_{REF} R^{2j}_{REF} F_R^{-2} P_r^2$, where $R_{REF}$
is the slant-range reference distance, $j$ is the reference slant
range exponent, $\alpha_{REF}$ is the reference incidence angle, $F_R$
is the rescaling factor, $K$ is the calibration constant, and
$P_r$ is the CSK image amplitude value. Both CSK image
were coregistered using the ENVI 4.7 software, using both
automatic and manual control points.

A. Assessed methodologies

For the following three methods, coregistered SAR intensity
images acquired at different dates were analyzed, and a map
identifying the intensity of the change between images
(change map) was developed. All the methods used a $7 \times 7$
sliding window, and the implementations were carried out in
the R platform (http://www.r-project.org/) for enhanced
numerical properties [12].

1) Generalized Likelihood Ratio Test (GLRT) [1]: This
methodology is based on testing $H_0$ : there is no change
against $H_1$ : the first image intensity comes from an underly-
ing reflectivity $\lambda_1$ which is different from the reflectivity of
the second image $\lambda_2$.

Homogeneous areas in intensity format can be described
by using the multiplicative model [13]. Torres et al. [14]
model the heterogeneity using a Gamma distribution allowing
the number of looks to vary locally. The distribution of the
observed multilook intensity data follows, then, a gamma random variable with density

\[ f_Z(z; L, \lambda) = \frac{L^L}{\lambda^L \Gamma(L)} z^{L-1} \exp\left\{ -\frac{Lz}{\lambda} \right\}, \]

where \( \Gamma \) is the gamma function, \( z, \lambda > 0 \) and \( L > 0 \) is the equivalent number of looks.

The maximum likelihood estimators based on the sample \( Z_1, \ldots, Z_n \) of random variables are the sample mean \( \hat{\lambda} = n^{-1} \sum_{i=1}^{n} Z_i \) and the solution of the non-linear equation

\[ \ln \hat{L} - \psi^0(\hat{L}) - \ln n^{-1} \sum_{i=1}^{n} Z_i + n^{-1} \sum_{i=1}^{n} \ln Z_i = 0, \]

where \( \psi^0 \) is the digamma function.

Assuming that the intensity follows a Gamma distribution, a maximum likelihood ratio test can be computed, comparing the likelihood of \( H_0 \) to the likelihood of \( H_1 \). As defined by [1], considering a series of only two images, the difference of log-likelihood between \( H_1 \) and \( H_0 \) is \( \Delta H = L(2 \log 2 - 2 \log (1 + R) + \log R) \), where \( R = \lambda_1/\lambda_2 \) is the ratio of the mean reflectivities.

The equivalent number of looks \( L \) was computed in two ways:

1. \( GLRT_a \): by maximum likelihood [11],
2. \( GLRT_b \): by the sample coefficient of variation \( ENL = (\hat{\mu}/\hat{\sigma})^2 \) [15].

2. \( MIMOSA \) [10]: It detects outliers in a bi-dimensional plot of the arithmetic (AM) and geometric means (GM) compared to the predicted joint distributions for Fisher distributed data (amplitude data was obtained from intensity CSK data). In this approach, both the temporal arithmetic mean \( AM = (A_1 + A_2)/2 \) and the temporal geometric mean \( GM = (A_1 A_2)^{1/2} \) were calculated, where \( A_1 \) and \( A_2 \) are amplitude bands at times 1 and 2, respectively. The Fisher distribution functions (for both AM and GM) were fitted using the \texttt{fitdist} R package.

3. \( HD \) based on stochastic distances [11]: Hypothesis test methods are used to quantifying the contrast between regions. Two samples (sliding windows) at different times can be modeled with the random variables \( Z_1 \) and \( Z_2 \) with densities \( f_{Z_1}(z, \theta_1) \) and \( f_{Z_2}(z, \theta_2) \) respectively, and parameters \( \theta_1 = (L_1, \lambda_1) \) and \( \theta_2 = (L_2, \lambda_2) \). It is possible to obtain tests statistics based on stochastic distances for the hypothesis \( H_0 : \theta_1 = \theta_2 \) [16]. We used the Hellinger test statistic under the Gamma model, defined in [11] as:

\[ S_H = \frac{8mn}{m + n} \left( 1 - \frac{2^{(\hat{L}_1 + \hat{L}_2)} (\hat{\lambda}_1 \hat{\lambda}_2)^{\frac{\hat{L}_1 + \hat{L}_2}{2}}}{(\hat{\lambda}_1 + \hat{\lambda}_2)^{\frac{\hat{L}_1 + \hat{L}_2}{2}}} \right), \]

which is asymptotically distributed as a \( \chi^2_2 \) random variable.

B. Performance evaluation

Selected regions of change and no-change between images were chosen to serve as reference. The areas were identified using control sites from three Landsat 5 TM images dated at April 24, June 11 and October 17, 2011 (PATH 224, ROW 78) and a Google Earth image of April 7, 2011.

The following changes types were considered: 1) from vegetation to bare soil, 2) from vegetation to urban cover, 3) from bare soil to plowed soil, 4) from vegetation to flooded. Two no-changes types were identified: 1) native vegetation zones, 2) calm water zones. Evaluation was carried out building ROC curves for each methodology.

III. RESULTS

Fig. 2 presents the change maps derived using \( GLRT_a \), \( MIMOSA \), and \( HD \) methodologies; \( GLRT_a \) and \( GLRT_b \) produced very similar maps, therefore only the former is shown.

Fig. 3 shows the ROC curves for each method: \( GLRT_a \) in red, \( HD \) in blue, and \( MIMOSA \) in black. \( GLRT_a \) and
GLRTb produced very similar curves, therefore only the former is shown. Both, the corresponding areas under the ROC curves (AUC) and the optimized thresholds are tabulated in Table I. Youden’s J statistic [17] was employed in order to find the optimal cut-off: the threshold that maximizes the distance to the identity (diagonal) line. The optimality criterion is, thus, max\{sensitivity + specificity\}.

<table>
<thead>
<tr>
<th>Methodology</th>
<th>AUC</th>
<th>Threshold selected</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLRTa</td>
<td>0.959</td>
<td>-1.764</td>
</tr>
<tr>
<td>GLRTb</td>
<td>0.954</td>
<td>-1.678</td>
</tr>
<tr>
<td>MIMOSA</td>
<td>0.569</td>
<td>0.538</td>
</tr>
<tr>
<td>HD</td>
<td>0.955</td>
<td>65.908</td>
</tr>
</tbody>
</table>

In order to explain the deficient results obtained with MIMOSA, we identified the control regions of change and no-change in the GM–AM scatter plots of the temporal images. Fig. 4 shows the values of those ground truth pixels that did not change in blue, those ground truth pixels that changed appear in red.

Pixels that did not changed, for example calm water pixels marked as blue, are close to the straight line of slope 1, while the areas that changed have values not very far from this diagonal. In the work by Quin et al. [10], departures from the joint $G^0$ distribution (which they call “Fisher” [16]), are associated to change but, in our data, such departures were not observed.

IV. CONCLUSIONS

Methods based on the Generalized Likelihood Ratio Test and stochastic distances presented similar very good performance. They both are based on the assumption that intensity SAR data can be fitted by Gamma distribution models. The results highlight the use of these methodologies for change detection in CSK data. However, it was observed in the change maps obtained with both procedures that homogeneous zones (like calm water bodies) present more sensitivity to small changes. It is possibly due to the better fitting of Gamma model in those areas. Areas with different texture levels will be analyzed using specific and suitable approaches and distributions.

MIMOSA assumes an underlying $G^0$ distribution for amplitude data, and identifies changes in those observations.
which depart from the diagonal of the GM–AM scatter plot [10]. Pixels aggregated in a given image parcel that shows a certain level of change are not beyond the joint pdf (as demonstrated by their location in the GM–AM scatter plot) as suggested by [10]. In this way, MIMOSA calculation fails at detecting those changes. It seems that this method would be only suitable to detect pixels whose change in amplitude is noticeable, like change from/to urban pixels.

A relevant point to be considered in further works is the way to select optimal window sizes to detect changes. As in any statistically-based image processing procedure, large windows are desired to obtain accurate estimates, but small windows are required in order to grant observations without contamination. Moreover, a future issue is to improve threshold determination on change maps. It would be also interesting to assess the relationship between the optimized thresholds here obtained and the different change types defined.

REFERENCES


