CHANGE DETECTION ON SAR IMAGES USING DIVISIVE NORMALIZATION-BASED IMAGE REPRESENTATION

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ABSTRACT

In the context of multi-temporal synthetic aperture radar (SAR) images for earth monitoring applications, one critical issue is the detection of changes occurring after a natural or anthropic disaster. In this paper, we propose a new similarity measure for automatic change detection based on a divisive normalization image representation. The divisive normalization transform (DNT) has been recognized as a successful methodology to model the perceptual sensitivity of biological vision and a useful image representation that significantly reduces statistical dependence of natural images. In this work, we exploit the fact that the histogram of DNT coefficients within wavelet subbands can often be well fitted with a zero-mean Gaussian density function, which is a one-parameter function that allows efficient change detection of SAR images. The proposed change detector is compared to other recent modelbased approaches. Tests on real data show that our detector outperforms previously suggested methods in terms of the rate of false alarm rate and the total error rate.

Index Terms—change detection, Divisive normalization, Gaussian scale mixture, synthetic aperture radar (SAR) images.

I. INTRODUCTION

Detecting temporal changes occurring on the earth surface by observing them at different times is one of the most important applications of remote sensing technology. Especially, due to the all-weather operating ability of synthetic aperture radar (SAR) imagery, multi-temporal SAR image change detection has many applications, such as environmental monitoring, agricultural surveys, urban studies, and forest monitoring [1]. One critical issue in multi-temporal SAR images is the detection of changes occurring after a natural or anthropic disaster.

Over the years, many methods were proposed to solve this problem in the literature. The existing methods mainly fall into two categories: bi-temporal change detection and image time series change detection [2], [3]. Furthermore, most bitemporal change detection techniques can be classified into supervised [4] and unsupervised change detection methods [5]. In this paper, we only consider the unsupervised change detection process for two images acquired at different time. In general, most unsupervised change detection methods include three steps: 1) preprocessing, such as despeckling and image registration, 2) image comparison to generate a difference image, and 3) thresholding the difference image to compute the final binary change detection map [6]–[8]. In this paper, we choose to focus on the second step, where the objective is to find a good detector to measure the degree of the similarity at each pixel between two image data. For the thresholding method, the method in [6] is adopted to generate the final change map.

For image comparison, several detectors have been proposed. The classical detectors include differencing and ratioing techniques [1], which are carried out through pixel-by-pixel comparison. Compared to the difference operator, the ratio operator is more robust to illumination variation, speckle noise and calibration errors. However, the ratio operator, also known as the mean ratio detector introduced by Ulaby [9], assumes that the texture is a zero-mean multiplicative contribution. As a result, it cannot detect changes taking place at the texture level. In recent years, promising methods based on information measures have been proposed, where the local probability density functions (pdfs) of the neighborhood of pixels of the pair images are compared, instead of a pixelby-pixel comparison. In [10], the Gaussian model has been used to approximate the local pdf. In [11], two more flexible models including the Pearson system, which is composed of eight types of distributions, and one-dimensional Edgeworth series expansion techniques, were proposed to estimate local statistics. Note that all of these aforementioned distributions are only dedicated to SAR images corresponding to a specific landcover typology. However, the actual SAR image can, in general, show a varied scene presenting several distinct land-cover typologies. In order to solve this problem, the Gaussian mixture model was proposed by the authors in [12] to model the SAR image in a locally adaptive manner since it can approximate a variety of distributions and is suitable to model different regions with different characteristics in the SAR image.

However, all the aforementioned methods are performed in the spatial domain. The method proposed in [13] extends the information measure-based methods to the wavelet domain by using generalized Gaussian (GGD) and generalized Gamma (GTD) distributions to model the subband coefficient magnitudes. Although the method introduced in [13] achieved notable success, there are some drawbacks of this paper. First, the GGD and GTD are single parametric mathematical distribution models, which can only be used to approximate the local statistics when the neighborhood of each pixel belong to one homogenous region corresponding to a specific land-cover typology. However, the actual SAR image can, in general, show a varied scene representing several distinct land-cover typologies. Second, the neighboring wavelet coefficients have strong highorder statistical dependencies [14]. But the method in [13] did not utilizes this property. Third, the wavelet decomposition is restrictive due to its linear nature and cannot represent possible nonlinear effects [14].

In this paper, we propose a new image comparison method that is inspired by the recent success of the divisive normalization transform (DNT) as a statistically and perceptually motivated image representation [15], [16]. This local gaincontrol divisive normalization model is well-matched to the statistical prosperities of optical images, as well as the perceptual sensitivity of the human visual system [17], [18]. The DNT is built upon linear transform models, where each coefficient (or neuronal response) is normalized (divided) by the energy of a cluster of neighboring coefficients (neighboring neuronal response) [14]. This procedure can explain nonlinearities in the responses of mammalian cortical neurons, and nonlinear masking phenoma in human visual perception, and was also empirically shown to produce approximately Gaussian marginal distributions and to reduce the statistical dependencies of the original linear representation [19]. Therefore, we proposed a change detection method for SAR images in the DNT domain rather than in the wavelet domain due to the superior properties of the DNT as mentioned above. This paper is organized as follows. The divisive normalization transform for SAR image is described in Section II. Section III presents the proposed image comparison algorithm based on the DNT image representation. Section IV presents the results on real data using the proposed detector. Finally, conclusions are drawn in Section V.

II. DIVISIVE NORMALIZATION-BASED IMAGE REPRESENTATION

In computational vision science, the current models of early visual processing in the human cortex involve two stages [18]:

$$x \xrightarrow{T} w \xrightarrow{R} y \tag{1}$$

where the image x is first analyzed by a linear image decomposition T and then followed by a non-linear transform (the divisive normalization) R. Here, the wavelet image decomposition is employed as the linear image decomposition model since it provides a convenient framework of localized representation of images simultaneously in space, frequency (scale) and orientation [20]. Let w and y represent wavelet and DNT coefficients, respectively, and y = w/z, where z is the positive divisive normalization factor that is calculated as the energy of a cluster coefficients that are neighbors of the coefficient y in space, scale, and orientation.

In the literature, several approaches [16], [19], [21] were proposed to compute the normalization factor z. Among these approaches, the convenient estimation method in [22] is adopted. This method derives the factor z through the Gaussian scale mixtures (GSM) model. A random vector W is a GSM if it can be expressed as the product of two independent components: W = zU, where the mixing multiplier z is a positive scalar random variable; $U \sim N(0, Q)$ is a zero-mean Gaussian random vector, and z and U are independent. As a consequence, any GSM variable has a density given by an integral [22]:

$$p_W(W) = \int \frac{1}{[2\pi]^{N/2} |z^2 Q|^{1/2}} \exp(-\frac{W^T Q^{-1} W}{2z^2}) \phi_z(z) dz \quad (2)$$

where N is the length of the GSM random vector W, and $\phi_z(z)$ is the probability density of the mixing variable z. The GSM model expresses the density of a random vector as a mixture of Gaussians with the same covariance structure Q but scaled differently by z [14]. A special case of a GSM is a finite mixture of Gaussians, where z is a discrete random variable. This GSM model was shown to represent well the statistics of the wavelet coefficients of images, where the vector W is formed by clustering a set of neighboring wavelet coefficients within a subband, or across neighboring subbands in scale and orientation [22]. The GSM model has also found successful applications such as image coding [21], image denoising [23], image restoration [24], and image quality assessment [20].

For our application, the wavelet coefficients of SAR images are modeled as a GSM random vector W that is formed by clustering a set of neighboring wavelet coefficients within a subband and that is normalized by the mixing multiplier. The general form of the GSM model allows for the mixing multiplier z to be a continuous random variable at each location of the wavelet subbands. To simplify the model, we assume that z only takes a fixed value at each location (but varies over space and subbands). The benefit of this simplification is that when z is fixed, W is simply a zero-mean Gaussian vector with covariance z^2Q . Thus, it becomes simple to estimate the normalization factor z in the DNT representation from the neighboring coefficients. The coefficient cluster W moves step by step as a sliding window across a wavelet subband, resulting in a spatially varying normalization factor z [14]. In our implementation, the normalization factor computed at each step is only applied to the center coefficient w_c of the vector W, and the normalized coefficient becomes $y_c = w_c/\hat{z}$, where \hat{z} is the estimation of z. An efficient method to obtain \hat{z} is by a maximum-likelihood estimation [22] given by

$$\hat{z} = \arg \max_{z} \{ \log p(z|W) \}$$

$$= \sqrt{W^T Q^{-1} W/N}$$
(3)

where $Q = E[UU^T]$ is the positive definite covariance matrix of the underlying Gaussian vector U and is estimated from the entire wavelet subband before estimating local z, and N is the length of vector W, or the size of the sliding window of the neighboring wavelet coefficients [14].

Before the development of the specific change detection algorithm, it is useful to observe variations of image statistics before and after the DNT. In Fig. 1, we compare the distributions of original wavelet subbands and the same subbands



Fig. 1. (a),(f): Original SAR images; (b),(g): Wavelet coefficients; (c),(h): PDFs of wavelet coefficients (solid curves) fitted with a Gaussian model (dashed curves); (d),(i): DNT coefficients; (e),(j): PDFs of DNT coefficients (solid curves) fitted with a Gaussian model (dashed curves).



Fig. 2. The block diagram of the proposed change-detection algorithm.

after DNT, for a pair of SAR images. In Figs. 1 (c) & (h), the original wavelet coefficient distributions of the SAR images are fitted using a Gaussian model. The noticeable difference between the two curves (the actual pdf and the fitted Gaussian model) shows that the original wavelet coefficients are highly non-Gaussian. In contrast, as shown in Figs.1 (e) & (j), the distribution of the coefficients after DNT can be well fitted with a Gaussian. A similar conclusion is obtained for other SAR images.

III. CHANGE DETECTION IN THE DNT DOMAIN

Let us consider two co-registered SAR intensity images I_{X1} and I_{X2} acquired over the same geographical area at two different times t_{X1} and t_{X2} , respectively [11]. Our aim is to generate a change detection map that represents changes that occurred on the ground between the acquisition dates [11]. This change detection problem can be modeled as a binary classification problem where 1 represents changed pixels and 0 represents unchanged pixels.

We propose a change detection algorithm by analyzing the difference of local statistics of the DNT coefficients of two acquired SAR images. A pixel will be considered as a changed pixel if the local statistical distribution of the DNT coefficients changes from one image to the other. In order to quantify this change, the Kullback-Leibler (KL) divergence [25] between two probability density functions is used. The framework of the proposed method in the wavelet domain is shown in Fig. 2. The first step is to decompose a sliding window at each pixel into multiple subbands by using the wavelet transform. Then, the DNT is performed for each subband. The third step is to estimate for each subband the parameters (mean and variance of the Gaussian distribution) governing the distribution of DNT coefficients. The fourth step is to compute the symmetric KL divergence between the estimated Gausssian PDFs of two subbands at the same level and orientation. Thus, the similarity map for each pair of subbands at the same level and orientation is obtained. Finally, all the subband-specific similarity maps are combined to obtain a final similarity map $SMAP(n_1, n_2)$ by summing the similarity maps over all subbands as follows:

$$SMAP(n_1, n_2) = \sum_{i=1}^{L} \sum_{j=1}^{M} D(p_{y_1;i,j} \| p_{y_2;i,j})$$
(4)

where (n_1, n_2) is the location of the pixel where the sliding window is centered; *L* and *M* are the numbers of the scales and orientations, respectively; and $p_{y_1;i,j}$ and $p_{y_2;i,j}$ are the estimated distributions of DNT coefficients at scale *i* and orientation *j* for the considered local windows being compared.



Fig. 3. Multitemporal ERS2 SAR images used in the experiments: (a) image acquired in April 1999 before the flooding; (b) image acquired in May 1999 after the flooding; (c) the ground truth change map used as reference in the experiments.



Fig. 4. Change detection results from different algorithms on SAR image dataset: (a) GGDD [13]; (b) GΓDD [13]; (c) GMMD [12]; (d) proposed method.

D is the symmetric KL distance and is given by [11]:

$$D(p_{y_1}, p_{y_2}) = KL(p_{y_1} || p_{y_2}) + KL(p_{y_2} || p_{y_1})$$
(5)

where $KL(p_{y_1}||p_{y_2})$ is the KL-divergence between p_{y_1} and p_{y_2} , also known as the relative entropy, and is given by [25]:

$$KL(p_{y_1} || p_{y_2}) = \int p_{y_1}(y) \log \frac{p_{y_1}(y)}{p_{y_2}(y)} dy.$$

As described earlier, since the divisive normalization transform produces approximately Gaussian distributions, by using the Gaussian model in (5), the symmetric KL divergence can be computed as:

$$D(p_{y_1}, p_{y_2}) = \frac{\sigma_{y_1}^4 + \sigma_{y_2}^4 + (\mu_{y_1} - \mu_{y_2})^2 (\sigma_{y_1}^2 + \sigma_{y_2}^2)}{2\sigma_{y_1}^2 \sigma_{y_2}^2} - 1 \quad (6)$$

where μ_y and σ_y are, respectively, the mean and standard deviation of y. In our application, μ_y and σ_y are always equal to zero because of the DNT produce approximately zero-mean Gaussian distributions. The final binary change detection map is obtained by thresholding the similarity map $SMAP(n_1, n_2)$.

IV. RESULTS WITH REAL DATA

Experiments are performed on a real multi-temporal SAR dataset. As shown in Figs. 3 (a) & (b), this SAR dataset includes two regions acquired by the European Remote Sensing 2 (ERS2) satellite SAR sensor over an area near the city of Bern, Switzerland, in April and May 1999, respectively [6]. Between the two acquisition dates, the river flooded parts of the cities of Thun and Bern and the airport of Bern entirely. The corresponding ground truth change map between these two images is shown in Fig. 3 (c).

The effectiveness of the proposed change detection algorithm is assessed by comparing with other start-of-the-art

Table I. False detections, missed detections, and total errors (in number of pixels and percentage) resulting from different change detection algorithms on SAR image dataset.

| Detector | False detections | | Missed detections | | Total errors | |
|------------|------------------|-------|-------------------|--------|--------------|-------|
| | Pixels | % | Pixels | % | Pixels | % |
| GGDD [13] | 8051 | 9% | 66 | 5.71% | 8117 | 8.96% |
| GΓDD [13] | 3602 | 4.03% | 270 | 23.38% | 3872 | 4.27% |
| GMMD [12] | 1884 | 2.11% | 184 | 15.93% | 2068 | 2.28% |
| Our method | 486 | 0.54% | 297 | 25.71% | 783 | 0.86% |

methods as shown in Fig. 4. The change detection maps shown in Figs. 4 (a) & (b) are obtained by using respectively, the wavelet-based GGD detector (GGDD) and GFD detector (GFDD) [13]. The change detection map shown in Fig. 4 (c) is obtained by using the state-of-the-art GMM detector (GMMD) of [12] in the spatial domain. The result of our proposed method is shown in Fig. 4 (d). Note that the same thresholding method [6] is used for all these detectors in order to obtain the final change map. The window size for all methods is fixed to 13×13 . For the multi-scale based detectors, the sliding window is decomposed into L = 3 scales using an undecimated wavelet transform with a Daubechies filter bank (in our implementation, a db 2 filter bank is used). From Fig. 4, it is clear that GMMD and the proposed method exhibit much better performance than the GGDD and GFDD.

In order to perform quantitative measurement, the false detection error, missed detection error and total error are measured by using the obtained binary change detection mask together with the ground truth change detection map. The false alarm rate P_{FA} is computed in percentage as P_{FA} = $N_{FA}/N_{unchange} \times 100\%$, where N_{FA} is the total number of detected false alarm pixels and $N_{unchange}$ is the total number of unchanged pixels in the ground truth change detection map. The missed detection rate $P_{MD} = N_{MD}/N_{change} \times 100\%$, where N_{MD} is the total number of changed pixels that were not detected and N_{change} is the total number of change pixels in the ground truth change detection map. The total error rate $P_{TE} = (N_{FA} + N_{MD})/(N_{unchange} + N_{change}) \times 100\%$. Table I summarizes those three errors for each detector. From Table I, it can be seen that the proposed detector produces the lowest total error rate of 0.86%.

V. CONCLUSION

In this paper, we proposed a novel change detection algorithm using statistical features of the divisive normalizationbased image representation. Compared to existing detectors with higher-order statistics, the proposed method exhibits lower computational complexity with better change detection performance in terms of total error rate.

VI. REFERENCES

- E. J. M. Rignot and J. J. van Zyl, "Change detection techniques for ERS-1 SAR data," *IEEE Trans. Geosci. Remote Sens.*, vol. 31, no. 4, pp. 896 –906, July 1993.
- [2] B. P. Salmon, J. C. Olivier, K. J. Wessels, W. Kleynhans, F. van den Bergh, and K. C. Steenkamp, "Unsupervised land cover change detection: Meaningful sequential time series analysis," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.* (JSTARS), vol. 4, no. 2, pp. 327C335, 2011.
- [3] K. S. Chen, H. W.Wang, C. T.Wang, and W. Y. Chang, "A study of decadal coastal changes on western taiwan using a time series of ERS satellite SAR images," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens. (JSTARS)*, vol. 4, no. 4, pp. 826–835, 2011.
- [4] L. Bruzzone and D. F. Prieto, "An adaptive semiparametric and context-based approach to unsupervised change detection multitemporal remote-sensing images," *IEEE Trans. Image Process.*, vol. 11, no. 4, pp. 452C466, Apr. 2002.
- [5] L. Bruzzone and D. F. Prieto, "Automatic analysis of the difference image for unsupervised change detection," *IEEE Trans. Geosci. Remote Sens.*, vol. 38, no. 3, pp. 1171C1182, May 2000.
- [6] Y. Bazi, L. Bruzzone, and F. Melgani, "An unsupervised approach based on the generalized gaussian model to automatic change detection in multitemporal SAR images," *IEEE Trans. Geosci. Remote Sens.*, vol. 43, no. 4, pp. 874–887, Apr. 2005.
- [7] T. Celik, "A bayesian approach to unsupervised multiscale change detection synthetic aperture radar images," *Signal Process.*, vol. 90, no. 5, pp. 1471–1485, May 2010.
- [8] Y. Bazi, L. Bruzzone, and F. Melgani, "Image thresholding based on the EM algorithm and the generalized gaussian distribution," *Pattern Recogn.*, vol. 40, no. 2, pp. 619–634, 2007.
- [9] F. T. Ulaby, F. Kouyate, B. Brisco, and T. H. L. Williams, "Textural information in SAR images," *IEEE Trans. Geosci. Remote Sens.*, vol. GRS-24, no. 2, pp. 235 –245, Mar. 1986.
- [10] V. Frost, J. Stiles, K. Shanmugan, and J. Holtzman, "A model for radar images and its application to adaptive digital filtering of multiplicative noise," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-4, no. 2, pp. 157–165, Mar. 1982.
- [11] J. Inglada and G. Mercier, "A new statistical similarity measure for change detection in multitemporal SAR images and its extension to multiscale change analysis," *IEEE Trans. Geosci. Remote Sens.*, vol. 45, no. 5, pp. 1432 –1445, May 2007.
 [12] Qian Xu and Lina J Karam, "Change detection on sar images by
- [12] Qian Xu and Lina J Karam, "Change detection on sar images by a parametric estimation of the kl-divergence between gaussian mixture models," in Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on, 2013, pp. 2109–2113.
- [13] S. Cui and M. Datcu, "Statistical wavelet subband modeling for multi-temporal SAR change detection," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 5, no. 4, pp. 1095–1109, 2012.
 [14] Qiang Li and Zhou Wang, "Reduced-reference image quality
- [14] Qiang Li and Zhou Wang, "Reduced-reference image quality assessment using divisive normalization-based image representation," *IEEE Journal of Selected Topics in Signal Processing*, vol. 3, no. 2, pp. 202–211, 2009.
- [15] Eero P Simoncelli and Bruno A Olshausen, "Natural image statistics and neural representation," *Annual review of neuroscience*, vol. 24, no. 1, pp. 1193–1216, 2001.
- [16] Odelia Schwartz and Eero P Simoncelli, "Natural signal statistics and sensory gain control," *Nature neuroscience*, vol. 4, no. 8, pp. 819–825, 2001.
- [17] David J Heeger, "Normalization of cell responses in cat striate cortex," *Visual neuroscience*, vol. 9, no. 02, pp. 181–197, 1992.
- [18] Eero P Simoncelli and David J Heeger, "A model of neuronal responses in visual area mt," *Vision research*, vol. 38, no. 5, pp. 743–761, 1998.
- [19] Siwei Lyu and Eero P Simoncelli, "Statistically and perceptually motivated nonlinear image representation," in *Electronic Imaging 2007*. International Society for Optics and Photonics, 2007,

pp. 649207-649207.

- [20] Abdul Rehman and Zhou Wang, "Reduced-reference image quality assessment by structural similarity estimation," *IEEE Transactions on Image Processing*, vol. 21, no. 8, pp. 3378– 3389, 2012.
- [21] Jesús Malo, Irene Epifanio, Rafael Navarro, and Eero P Simoncelli, "Nonlinear image representation for efficient perceptual coding," *IEEE Transactions on Image Processing*, vol. 15, no. 1, pp. 68–80, 2006.
- [22] Martin J Wainwright and Eero P Simoncelli, "Scale mixtures of gaussians and the statistics of natural images.," in *NIPS*. Citeseer, 1999, pp. 855–861.
- [23] Javier Portilla, Vasily Strela, Martin J Wainwright, and Eero P Simoncelli, "Image denoising using scale mixtures of gaussians in the wavelet domain," *IEEE Transactions on Image Processing*, vol. 12, no. 11, pp. 1338–1351, 2003.
- [24] Javier Portilla and Eero Simoncelli, "Image restoration using gaussian scale mixtures in the wavelet domain," in *IEEE International Conference on Image Processing*, 2003. ICIP 2003., 2003, vol. 2, pp. II–965.
- [25] S. Kullback and R. A. Leibler, "On information and sufficiency," *Ann. Math. Stat.*, vol. 22, no. 1, pp. 79–86, Mar. 1951.