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An automatic change detection approach for rapid flood mapping in Sentinel-1 SAR data

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ABSTRACT

In this paper, a two-step automatic change detection chain for rapid flood mapping based on Sentinel-1 Synthetic Aperture Radar (SAR) data is presented. First, a reference image is selected from a set of potential image candidates via a Jensen-Shannon (JS) divergence-based index. Second, saliency detection is applied on log-ratio data to derive the prior probabilities of changed and unchanged classes for initializing the following expectation-maximization (EM) based generalized Gaussian mixture model (GGMM). The saliency-guided GGMM is capable of capturing the primary pixel-based change information and handling highly imbalanced datasets. A fully-connected conditional random field (FCRF) model, which takes long-range pairwise potential connections into account, is integrated to remove the ambiguities of the saliency-guided GGMM and to achieve the final change map. The whole process chain is automatic with an efficient computation. The proposed approach was validated on flood events at the Evros River, Greece and the Wharfe River and Ouse River in York, United Kingdom. Kappa coefficients (k) of 0.9238 and 0.8682 were obtained respectively. The sensitivity analysis underlines the robustness of the proposed approach for rapid flood mapping.

1. Introduction

Floods are one of the most frequent and destructive natural disasters on earth. Earth Observation (EO) data enable the mapping of flood extent over large areas, providing the key information to disaster management authorities timely. Contrary to optical data, which are heavily affected by the weather condition, satellite-based synthetic aperture radar (SAR) data are of special attraction in disaster monitoring because of their day/night and all-weather image collection ability.

Change detection based on multi-temporal SAR images is widely used for disaster monitoring (Bovolo and Bruzzone, 2007; Gamba et al., 2007; Martinez and Le Toan, 2007; Martinis et al., 2011) as disasters like flood events are usually marked by abrupt changes on the land surface. Compared to flood mapping with a single image (Twele et al., 2016), change detection based methods have an advantage in masking out the permanent water bodies and some water look-alike objects. At least two images from the same sensor, with the same orbit track, the same polarization, and the same coverage are required for change detection, namely the reference image (pre-event) and the target image (co-event), respectively. In the literature, the reference image is usually manually selected from images that have been acquired at the same season as the target image in past years (Ban and Yousif, 2012) or the latest available image prior to the event (O'Grady et al., 2011), depending on the application. Within the increasing volume of SAR data, e.g. from the Sentinel-1 mission of the European Space Agency (ESA), which has a high repetition rate (6 days) based on a constellation of two satellites configuration (Sentinel-1 A and Sentinel-1B), there is more choice for reference data selection from the huge archives. The selection process should be accomplished carefully, as the result of change detection is affected by the quality of the reference image (Matgen et al., 2011). To our knowledge, only a few studies addressed this issue (Hostache et al., 2012; Schlaffer et al., 2015).

Unsupervised change detection is most widely used due to the lack of training samples for supervised algorithms in real applications (Fernandez-Prieto and Marconcini, 2011). In general, unsupervised change detection is based on the difference image (change indicator), for which a proper unsupervised classification algorithm is adopted. There exist several unsupervised approaches for change detection in SAR data. Commonly the ratio (Rignot and van Zyl, 1993) or log-ratio operator (Ban and Yousif, 2012; Bazi et al., 2005; Bovolo and Bruzzone, 2005) is used as change indicator due to multiple speckle noise of SAR data. Other comparison operators like similarity measures based on the local probability density function (Cui et al., 2016; Inglada and Mercier,

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2007) have also been used in unsupervised change detection. The histogram-based thresholding (Bazi et al., 2005, 2007; Bovolo et al., 2008; Moser and Serpico, 2006) and distance-based clustering (Celik, 2009a; Giustarini et al., 2015; Li et al., 2015) are very frequently used to extract the changed information from the change indicator. However, these pixel-based methods fail to suppress speckle noise and thus lead to unsatisfactory results. As a result, several contextual based descriptors were introduced, like the mathematical morphology (Pulvirenti et al., 2011), Gabor feature representation (Li et al., 2015), and second-order texture parameters (Giustarini et al., 2015). Due to the complexity of these methods, they may not be the first choice in time-oriented cases. Region growing (Giustarini et al., 2013) is a widely used post-processing method to improve pixel-based performance. A major drawback of this method is that it heavily relies on the initial seed pixels and the predefined similarity criteria between pixels. This behavior makes it non-robust in some scenarios. If no seed pixels are detected in a region of interest, this region will be completely ignored during the region growing procedure. Alternatively, in several studies (Bruzzone and Prieto, 2000; Martinis et al., 2011; Moser et al., 2007; Moser and Serpico, 2009) the spatial-context information is extensively integrated by the Markov Random Field (MRF) model (Geman and Geman, 1984) to remove the noise and improve the change detection accuracy. Particularly, the graph-cut based inference with the high availability of tractable attracts more attention in change detection (Cao et al., 2018; Gong et al., 2014) recently. Conditional Random Field (CRF) (Lafferty et al., 2001) is another contextual based model which raises a lot of attention in the computer vision field (Shotton et al., 2006; Toyoda and Hasegawa, 2008; Verbeek and Triggs, 2007). As opposed to MRF, CRF is a discriminative framework which relaxes the assumption of the conditional independence of the observation space (Ban, 2016; He et al., 2004). Wegner et al. (2011) applied a CRF model for building detection with a combination of InSAR and optical images. Ding et al. (2014) proposed a CRF model for SAR image classification. Zhou et al. (2016) and Cao et al. (2016) applied CRF-based methods on change detection using optical satellite images. In spite of the advantages of the random field models in image classification and change detection, traditional random field models suffer the risk of removing fine structures due to their local-connected limitation (Schindler, 2012; Su et al., 2011). To overcome this drawback, Yousif and Ban (2014) introduced a nonlocal probability MRF model to enforce the global consistency in change detection with SAR data. However, the increased computational complexity makes it not suitable to deal with SAR images in applications such as rapid flood mapping over large areas. The higher-order potentials CRF (Kohli et al., 2009) and hierarchical CRF (Ladicky et al., 2009) have been proposed to incorporate the long-range connection based on segments or superpixels. The drawback of these models is that the final result relies on the accuracy of the segmentation. The reliability of the unsupervised segmentation algorithms cannot be guaranteed, especially when the image covers a very complex environment. Furthermore, the accuracy of unary potential plays a critical role for the final result during the implementation of random filed models (Schindler, 2012; Vineet et al., 2012). When random field modeling is applied to unsupervised change detection, the corresponding unary potential is commonly achieved by unsupervised classification algorithms. Zhou et al. (2016) and Cao et al. (2016) initialized the CRF model in optical image change detection with fuzzy c-mean clustering. However, fuzzy c-mean clustering is sensitive to data noise and performs poorly on imbalanced data, which is not uncommon in flood extent mapping with SAR data over large areas. Bruzzone and Prieto (2000) and Yousif and Ban (2014) employed the expectation-maximization (EM) based parametric statistical model for the MRF model initialization in SAR image change detection. Within their studies, some approximate knowledge of the change information in the study area from the user is needed, which means it is not fully automatic. Although the EM-based parametric statistical model is guaranteed to converge (Bilmes, 1998), accurate prior information is required to speed up the convergence and to improve the accuracy of parameters estimation, especially when the prior probabilities are highly imbalanced (Bazi et al., 2007; Glasbey, 1993; Naim and Gildea, 2012).

Summarizing the above, to achieve an accurate delineation of flooded area using an automatic change detection method in SAR data, the employed method should be equipped with the following features: a) be capable of selecting an adequate reference image; b) be capable of handling highly imbalanced distribution between flooded and unflooded area; c) be robust to speckle noise while preserving the detailed flooded information. The failure in any of the aforementioned perspective leads to a reduction of mapping accuracy. This paper aims at filling the gaps between these perspectives by introducing an automatic change detection processing chain for rapid flood mapping in Sentinel-1 SAR data. The proposed processing chain consists of two main steps: (1) a Jensen-Shannon (JS) divergence-based index is proposed for proper reference data selection from archive data; (2) a saliency-guided generalized Gaussian mixture model (SGGMM) is employed on the difference image based on step (1), followed by a fully- connected CRF (FCRF) model, which incorporates pairwise connections of all pixels with an efficient inference to refine the primary result. Experiments on flooding at the Ervos River, Greece, and the Wharfe and Ouse River in York, United Kingdom, prove the effectiveness and efficiency of the proposed method. In the case of change detection for flood mapping, two kinds of change could occur (i.e., the negative change caused by open water, and the positive change caused by flooded vegetation or flooded urban areas). It is also true that most cases of large-scale flooding are dominated by one type of change (Chini et al., 2017). The method proposed in this paper only deals with the negative change caused by open water in rural areas as it is the most common case in rapid flood mapping task and we leave the two-type change situations for our future work.

2. Method

As the reference image is crucial for change detection, the proposed method starts with the automatic reference image selection. The JS divergence-based reference image index is introduced first in this section. Subsequently, the saliency-guided generalized Gaussian model is applied, which extracts primary change information from the difference image. Finally, the fully-connected conditional random field is employed to achieve the final change detection result. The flowchart is shown in Fig. 1.

2.1. Reference image index

The reference image selection process consists of two steps. Firstly, some potential image candidates are collected from the Copernicus Open Access Hub, which should fulfill the following criteria: the data should be acquired from the same relative orbit and with the same polarization configuration as the flood image. Especially in regions with pronounced seasonal flooding, only images acquired in the same period of the year as the target image should be collected (Hostache et al., 2012). Secondly, the final reference image is selected from the collected images based on the reference index (describe later in this section). The optimal candidate should be acquired during a period without flood (noted as “non-flooded”) and should represent the “normal behavior” of the scene. It is worth to mention that too many collected potential candidates could

be time-consuming with the corresponding preprocessing and increase the storage burden as well, a too small volume of candidates will degrade the optimization of the final reference image. Considering the high temporal resolution (12 days for a single satellite and 6 days for the constellation of two satellites) of Sentinel-1 data and the systematic global acquisition plan of the satellite mission, it can be assumed that images acquired during the latest year prior to the flood could be a proper potential candidate set.