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A self-paced learning algorithm for change detection in synthetic aperture radar images[☆]

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ABSTRACT

Detecting changed regions between two given synthetic aperture radar images is very important to monitor change of landscapes, change of ecosystem and so on. This can be formulated as a classification problem and addressed by learning a classifier, traditional machine learning classification methods very easily stick to local optima which can be caused by noises of data. Hence, we propose an unsupervised algorithm aiming at constructing a classifier based on self-paced learning. Self-paced learning is a recently developed supervised learning approach and has been proven to be capable to overcome effectively this shortcoming. After applying a pre-classification to the difference image, we uniformly select samples using the initial result. Then, self-paced learning is utilized to train a classifier. Finally, a filter is used based on spatial contextual information to further smooth the classification result. In order to demonstrate the efficiency of the proposed algorithm, we apply our proposed algorithm on five real synthetic aperture radar images datasets. The results obtained by our algorithm are compared with five other state-of-the-art algorithms, which demonstrates that our algorithm outperforms those state-of-the-art algorithms in terms of accuracy and robustness.

1. Introduction

IMAGE change detection is a technology to detect changed and unchanged regions between images taken from the same place at different times, which helps following studies and analyses [1]. In many civil or military applications such as medical detection and treatment [2,3], remote sensing [4], and video surveillance [5,6], image change detection plays a vital role [7,8]. Change detection in SAR images is getting increased attention in recent years for the imaging characteristics of SAR, such as all-time, all-weather, and large-area [9]. SAR images can provide more information than ordinary optical ones [10], but it suffers from speckle noise [11]. Processing of SAR images with multiplicative speckle noises is very challenging [12]. Most developed unsupervised algorithms used for detecting the changes in SAR images can be divided into three steps [13]. First, a geometric correction and registration are usually implemented to transform two images into a same coordinate system. Next, a difference image (DI) is generated based on two SAR images. Log-ratio operator is a widely used method [14] for this purpose, which transforms a difference image into a logarithmic scale one and converts multiplicative noises into additive ones. Finally, they analyze the DI aiming at forming a classification to classify the changed regions between two SAR images. The quality of the generated DI plays a decisive role in the final result of the change detection of SAR images.

Two methods have been widely used for analyzing DI: (i) clustering methods and (ii) threshold methods. As for the clustering methods, fuzzy c-means clustering (FCM) is one of the most famous and classical one [15]. This method can retain more information than hard clustering. In this regard, Ahmed et al. [16] introduced the spatial neighborhood information by modifying the objective function in FCM_S causing a large time complexity. In order to speed up the running time, Szilagyi et al. [17] proposed the Enhanced FCM (EnFCM). Krindis Chatzis et al. [18] proposed robust fuzzy local information C-means clustering method (FLICM). Its main contribution was using a novel fuzzy local similarity measurement to alleviate the influence of noise and preserve more image detail with no parameter setting. Gong et al. [19] proposed a reformulated FLICM (RFLICM) to further reduce the effect of speckle noises by adding a fuzzy factor to the objective function. The clustering methods mentioned above can

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achieved good change detection maps, but they are affected by the speckle noises [20]. In addition, it is difficult to achieve the balance between preserving the details and suppressing the noise's effect.

Classical threshold methods mainly build a statistical model first for DI, and use algorithms such as Kittler Illingworth (KI) [21] or expectation maximization (EM) algorithm [22] to acquire an appropriate threshold. In this regard, Bruzzone et al. [23] proposed to use Gaussian distribution to model DI where an EM algorithm was used to find the threshold. The Markov random field (MRF) [24], the Fisher distribution [25], and the Nakagami distribution [26] were also used to model DI. Furthermore, the multinomial latent model [27] was applied on SAR images. Threshold method is easy to understand and simple to implement, but has a low accuracy. DI is complex because of the speckle noises, so methods mentioned above are hard to establish accurate models for DI.

Li et al. [28] recently proposed a new unsupervised algorithm utilizing some known change detection maps and the matching pursuit to learn a dictionary. Gong et al. [29] used deep learning to achieve change detection for SAR images. They select samples based on a pre-classification without using difference image. Deep learning was then used to learn high-order features and classify the SAR images. Deep learning has shown promising performance in classification problems and it achieves accurate results. The learning algorithms used to tackle change detection issues in SAR images can avoid the shortcomings of traditional clustering and threshold methods [29] to some extent. In recent years, machine learning methods plays more and more important role in many areas. Such as for handling a quadratic formulation with a pair of equality constraints, an interesting accurate on-line algorithm for training ν-support vector classification was proposed [30]. Two finite mixture models was proposed to capture the structural information of the data from binary classification and obtained good results were obtained [31]. A robust regularization path algorithm for ν-support vector classification was proposed and the proposed algorithm found effective experimental results [32]. Kernel technique was introduced to improve the existing quaternion principal component analysis and the improved algorithm obtained effective results [33]. Nonetheless, classical machine learning methods are sensitive to noises of the samples, and they also easily get stuck into local optima. Although deep learning methods are superior to tradition methods, they are also affected by noises and have a large complexity.

Self-paced learning (SPL) [34,35] has attracted huge attentions in recent years. SPL is useful for many problems such as specific-class segmentation [36], long-term tracking [37], and visual category discovery [38]. Meng et al. [39] gave a theory analysis for SPL, and they proved that SPL is robust to noisy samples and can address local optima problem. Because of the superiority of SPL on classification problems, many variations of SPL have been proposed [40]. Jiang et al. [40] proposed SPLD incorporating diversity of samples into basic SPL. Jiang et al. [41] used self-paced reranking method to deal with multimedia search problems. They proposed SPCL [42] combining self-paced learning and curriculum learning. In addition, Li et al. proposed [43] MLSPL incorporating the self-paced learning strategy into multi-label learning regimes to improve classification accuracy. Li et al. [44] proposed SPMTL incorporating self-paced learning into multi-task learning paradigm.

Self-paced learning has excellent performance on the classification problems due to its special learning mechanism. This can overcome the disadvantages of traditional learning algorithms mentioned above. But SAR image suffers from speckle noises and has spatial continuity, and these special characteristics make change detection of SAR image distinguish from other classification problems. Therefore, we propose a new self-paced learning algorithm combined with characteristics of SAR images to deal with the change detection issues in SAR images in order to achieve more accurate and more robust results. Our algorithm has the following characteristics: (i) this algorithm does not need labeled data. Self-paced learning is a supervised learning method, which needs labeled samples. However, for SAR image change detection, manually labeling each pixel consumes a lot of time and manpower. So the proposed algorithm first uses basic FCM to pre-classify the DI and selects some samples based on the classification result of FCM; (ii) In SAR image change detection, the gap between the number of changed pixels and the number of unchanged pixels is often very large. Our algorithm uniformly selects samples to avoid lacking samples in one specific class. In addition, our algorithm uses spatial continuity of SAR image to ensure the accuracy and diversity of samples; (iii) the feature of selected sample in the proposed algorithm is not a single pixel but a neighborhood, so the learning process can incorporate spatial information to enhance the robustness of the algorithm; (iv) after the classification of the classifier obtained by self-paced learning, a simple filter is used to smooth the final result. So, our proposed algorithm benefits from the characteristics of SAR images and the superiority of self-paced learning.

The rest of this paper is as follows: Section 2 describes the detail of self-paced learning algorithm for SAR images change detection. Introductions of datasets, evaluation criteria and parameter analysis are presented in Section 3 . Section 4 shows the experimental results of the proposed algorithm and five compared algorithms. And the conclusion of this paper is drawn in Section 5.

2. Methodology

Consider two co-registered SAR images $I_1=\{I_1(i,\ j),\ 1\le i\le A,\ 1\le j\le B\}$, $I_2=\{I_2(i,\ j),\ 1\le i\le A,\ 1\le j\le B\}$, which are captured from the same place at times t_1 and t_2 respectively. The main purpose of change detection is to identify the change of every pixel at time t_1 and t_2 represented by I_1 and I_2, which actually is a classification problem. This ultimately forms a binary image $I=\{I(i,\ j),\ 1\le i\le A,\ 1\le j\le B\}$ where the size of I, I_1 and I_2 are $A\times B$, $I(i,\ j)$ is 0 or 1 means that the corresponding pixel is unchanged or changed.

Recently, Bengio et al. [45] proposed curriculum learning raising widespread concern in machine learning and computer vision fields. Kumar et al. [31] proposed Self-paced learning that can be considered as a subset of the curriculum learning [30]. Inspired from the learning process of human, this approach initially learns from easier samples. Then, it gradually utilizes more complex samples. Many experiments have demonstrated that self-paced learning avoids sticking to a local optimum and results in an effective solution [46]. In this paper, we propose to use self-paced learning combined with the characteristics of SAR images to achieve the change detection of SAR images.

The main task of SPL is to obtain a classifier by minimizing an objective function as follows:

$$\min_{w,\nu} E(w,\nu;\lambda)=\sum_{i=1}^{m}\nu_i L(y_i, f(x_i,w))-\lambda\sum_{i=1}^{m}\nu_i \quad \text{s.t. } \nu\in[0,1]^m \tag{1}$$

where m is the number of samples, x_i is the i_{th} sample in the training set, y_i is the label of x_i, $f(x_i,w)$ denotes the model of the classifier and w is the parameter of the classifier. $L(y_i,\ f(x_i,w))$ is the cost function of x_i and indicates a difference between y_i and $f(x_i,w)$. $\boldsymbol{\nu}$ is an m-dimension vector, and ν_i is the i_{th} element which denotes the difficulty of sample x_i where $\nu_i=1$ means x_i is "easy", and $\nu_i=0$ means x_i is "complex". λ is an "age" parameter to determine whether a sample is "easy".

SPL is type of supervised learning which needs labeled samples, but labeling SAR images is a very difficult task in SAR image processing. To avoid this, we propose a unsupervised algorithm