Sea Ice Change Detection from Synthetic Aperture Radar Images Based on Self-Paced Boosting Learning

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***Abstract*—The change information of sea ice is important for navigation safety and natural resource extraction, and polar sea ice monitoring has drawn increasing attentions. In this paper, we focus on the problem of sea ice change detection from Synthetic Aperture Radar (SAR) images. Existing works usually treat the problem as a classification task. Recently, researchers noticed that humans and animals learn much better when the examples are organized in a meaningful order, and proposed Self-Paced Boost Learning (SPBL) to simulate the process. Inspired by this, we proposed a novel sea ice change detection method based on SPBL. First, log-ratio operator is utilized for difference image generation. Then, a hierarchical fuzzy c-means (FCM) clustering algorithm is employed to select reliable samples. Finally, based upon these samples, SPBL is employed to classify pixels from the original SAR images into unchanged and changed class. The quantitative and qualitative analysis on two real SAR datasets has demonstrated the effectiveness of the proposed method.**

***Index Terms*—synthetic aperture radar images; change detection; self-paced boost learning; feature classification**

I. Introduction

Sea ice information is very important for the safe navigation of vessels, since the amount of ice adversely impacts the friction against the hull of a vessel. Some vessel's path is often blocked by thick sea ice. Therefore, polar sea ice research has attracted increasing attention these years. Especially, global warming accelerates loss of sea ice, which threatens animals and people living in the Arctic. Polar sea ice research has raised global security concerns.

Synthetic aperture radar (SAR) sensors provide the capability for all-weather, day-and-night surveillance. In recent years, the rapid developments of SAR sensor make the collection of SAR data more convenient. With the reduction of revisit interval, multi-temporal SAR images from the same area provide reliable data source for change detection. SAR image change detection has become a hot research topic in remote sensing applications. However, SAR image is easily affected by speckle noises, and change detection from SAR images has been widely acknowledged as a challenge task.

SAR image change detection is usually treated as a classification task. Specifically, a difference image (DI) is first calculated by log-ratio operator. Then, pixels in the DI are classified into changed and unchanged class by expectation maximization algorithm [1], fuzzy c-means (FCM) clustering [2], and support vector machines [3], etc. Gao *et al.* [2] presented a hierarchical FCM clustering algorithm for SAR change detection. The FCM algorithm is implemented in a coarse-to-fine procedure, and the change detection performance can be improved by the algorithm. Wang *et al.* [3] presented a SAR image change detection method based on Laplacian SVM. Some labeled samples are selected from the DI. Laplacian SVM explores the change information from these samples, and the discriminative power in changed pixels identification is enhanced. Hou *et al.* [4] presented a novel SAR image change detection technique based on compressed projection. Nonsubsampled contourlet transform is used to reduce the noise of the DI, and compressed projection is employed to extract feature for each pixel. The final change map is generated by partitioning the feature vector into changed and unchanged class using k-means clustering. Gong *et al.* [5] proposed a reformulated fuzzy local information c-means clustering algorithm for changed and unchanged pixels classification. The spatial context information is incorporated in a fuzzy way for the purpose of enhancing the changed information. The speckle noise can also be reduced, and the results obtained by the algorithm exhibit lower errors than the original fuzzy c-means algorithm. Lv and Zhong [6] proposed a multifeature probabilistic ensemble conditional random field method for change detection. The interactions between neighborhood pixels and the structural properties of the ground objects are take into account. In the unary potential of random field, the morphological feature of the DI are combined using a probabilistic ensemble strategy, and the method can obtain good classification performance for high spatial resolution images. The aforementioned method have obtained good performance. However, if more advanced classification model is utilized, the change detection performance can be further improved.

Bengio *et al.* [7] noticed that humans and animals learn much better when the examples are organized in a meaningful order. The order illustrates gradually more concepts, and gradually more complex ones. Inspired by this phenomenon,

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they proposed curriculum learning which can guide training towards better regions in parameter space. Later, Zhao *et al.* [8] studied self-paced learning paradigm which dynamically incorporates samples into learning from easy ones from complex ones. Recently, Pi *et al.* [9] noticed that boosting and SPL are consistent in basic concepts. Both schemes are based on an asymptotic learning process from a weak state to a strong state. Furthermore, boosting methods tends to reflect the local patterns, while SPL tends to explore the data smoothly with more robustness. Considering these characteristics of SPL, they proposed Self-Paced Boosting Learning (SPBL). SPBL can encourage reliable samples while suppress negative samples. If such schemes can be utilized into SAR image change detection, the intrinsic discriminative patterns between change and unchange regions maybe captured while keep the reliability of the training samples.

In this paper, we presented a novel SAR image change detection framework. SPBL is first introduced into SAR image change detection. Some pixels with high probabilities to be changed or unchanged are selected as training samples. Image patch features are generated around these pixels and SPBL is utilized to classify all the pixels from the original multitemporal SAR images into changed or unchanged class. After classification, we can obtain the final change map. Experimental results on two real sea ice datasets demonstrate the good performance of the proposed method.

II. Methodology

The framework of the proposed method is illustrated in Fig. 1. It consists of three main steps: First, DI generation by the log-ratio operator. Secondly, hierarchical FCM algorithm is employed to select reliable samples. Finally, based upon these samples, SPBL is employed to classify pixels form the original SAR images into unchanged and changed class. In the remainder of this section, we will describe more details about the FCM and SPBL classification.

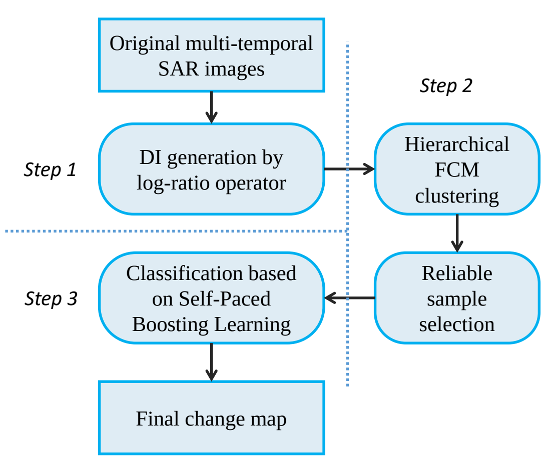


Fig. 1. Framework of the proposed change detection method

A. Hierarchical FCM clustering

The FCM algorithm [10] achieves the optimal partitioning of the samples by minimizing the objective function. Assuming that n samples are clustered into class c, the objective function is:

$$f=\sum_{i=1}^{n}\sum_{j=1}^{c}\eta_{ij}^{m}||x_i-y_j||^2, \tag{1}$$

where x_i is the eigenvector of sample i, y_j is the clustering center of j-th class, η_{ij} is the membership of sample i with respect to j, and m is the weight function. Here, the object function satisfies the constraint $\sum_{j=1}^{c}\eta_{ij}=1, i=1,2,\ldots,n$.

The FCM algorithm optimizes the objective function by updating y_j and η_{ij}. According to the Lagrange conditional extreme theory, the object function can be updated as follows:

$$\eta_{ij}=\frac{1}{\sum_{k=1}^{c}(\frac{||x_i-y_j||}{||x_i-y_k||})^{\frac{2}{m-1}}}, \tag{2}$$

$$y_{ij}=\frac{\sum_{i=1}^{n}\eta_{ij}^{m}x_i}{\sum_{i=1}^{n}\eta_{ij}^{m}}. \tag{3}$$

When the value of the objective function obtained by two adjacent iterations satisfies: $|f_t-f_{t-1}|<\epsilon$, it can be considered that a good clustering result has been obtained and the updating can be stopped. Here, ϵ is a small positive number called tolerance.

In this paper, after obtaining the DI by using the log-ratio operator, we partition pixels in DI into three groups: changed class Ω_c, unchanged class Ω_u, and intermediate class Ω_i. Pixels belonging to Ω_c and Ω_u have high probabilities to be changed or unchanged. Here, we use a hierarchical FCM clustering algorithm [2]. Specifically, the DI is first partitioned into five clusters. Then some intermediate clusters will be merged. Finally, we can obtain a preclassification change map denoted by $\{\Omega_c,\Omega_i,\Omega_u\}$. Then, pixels belonging to Ω_c and Ω_u are selected as reliable samples.

B. Classification by Self-Paced Boosting Learning

After obtaining reliable samples, neighborhood features of samples pixels are generated. Then, SPBL classifier is trained based on these features. Next, the neighborhood features of pixels belonging to Ω_i are fed into the pretrained classifier, and these pixels are classified into changed or unchanged class.

The SPBL does not directly classify, but instead asymptotically learns the advancing model from easy simple to complex samples. Let $\{(x_i,y_i)\}_{i=1}^{n}$ be the training samples, where $x_i\in\mathbb{R}^d$ is the feature of sample i, y_i is the class label of x_i. Therefore, the general objective of SPBL [9] can be formulated as:

$$\begin{gathered}\min_{w,u}\sum_{i=1}^{n}v_i\sum_{r=1}^{c}L(\rho_{ir})+\sum_{i=1}^{n}g(v_i;\lambda)+\nu R(W)\\ s.t.\ \forall i,r,\rho_{ir}=H_{i:}\omega_r;\ W\geq 0;\ v\in[0,1]^n,\end{gathered} \tag{4}$$

where v_i is assigned to each sample as a measure of weight, $H\in\mathbb{R}^{n\times z}$ is the weak classifiers' responses for the training data with $[H_{ij}] = [h_j(x_i)]$, and $H_{i:}$ is the i^{th} row of H. $s_i \in [0,1]$ is the self-paced learning weight of sample x_i that denotes its learning "easiness". $g(\cdot;\lambda) \to \mathbb{R}$ is the self-paced learning function that specifies how samples are selected. The function $g(s_i;\lambda)$ can dynamically select the easily learned samples that are more discriminative.

An alternating optimization can be used to solve the above equation. v and λ can be optimized with the other being fixed in an alternating manner. For the optimization of v, we can obtain:

$$v_i{}^* = \underset{v_i}{\arg\min}\, v_i l_i + g(v_i;\lambda),\ s.t.\ u_i \in [0,1], \tag{5}$$

where $l_i = \Sigma_r \ln(1 + e^{-\rho^{ir}})$ denotes the loss of samples x.

Jiang *et al.* [11] summarized the self-paced function. Firstly, $g(v_i;\lambda)$ is convex w.r.t. $v_i \in [0,1]$ to guarantee the uniqueness of v_i^*. Secondly, v_i^* is tuned to reduce the simple samples that can guarantee the less loss of choice. Finally, v_i^* increases monotonically, with high tolerance for losses. This can include more complex samples.

In addition, W can be optimized as follows:

$$\begin{aligned} W^* &= \underset{W}{\arg\min} \sum_{i,r} s_i \ln(1 + e^{-\rho_{ir}}) + \nu \|W\|_{2,1} \\ & s.t.\ \ \forall i, r, \rho_{ir} = H_{i:}w_{yi} - H_{i:}w_r;\ W \geq 0. \end{aligned} \tag{6}$$

To solve W in the above equation, the column generation method is employed, and the set of active weak classifiers is augmented. Detailed information about the SPBL algorithm can be found in Pi's work [9].

III. Experimental Results and Analysis

A. Experimental Setup

We will show the performance of the proposed method on two real SAR datasets. Both datasets are selected from two large SAR images of the region of the Sulzberger Ice Shelf. The images are captured by the European Space Agency Envisat satellite on March 11 and 16, 2011, respectively. Both images show the progression of the ice breakup. The ice breakup is triggered by Tohoku Tsunami in the Pacific Ocean on March 11 in 2011. The Tohoku Tsunami generates massive ocean waves. These waves caused the Sulzberger Ice Shelf to flex and break. We select two typical areas (256 × 256 pixels for each area) as the datasets. Both datasets and the available ground truth images which are obtained by integrating prior information with photo interpretation. Dataset I is shown in Fig. 1, and Dataset II is shown in Fig. 2.

The performance evaluation of change detection is a critical issue. First, we use false positives (FP), false negatives (FN), overall error (OE), percentage correct classification (PCC) and Kappa coefficient (KC) [12] as indicators to measure the effectiveness of the proposed method. The FP is the number of pixels that are unchanged pixels that are changed class in the ground truth image but wrongly classified as changed ones. The FN is the number of pixels that are changed class in the ground truth image but wrongly classified as unchanged ones. Nt is the number of pixels in the input image. Then the OE is computed by $\text{OE} = \text{FP} + \text{FN}$. The PCC is computed by $\text{PCC} = (Nt - \text{OE})/Nt \times 100\%$.

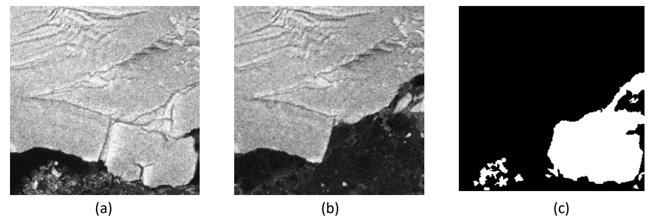


Fig. 2. Dataset I from Sulzberger Ice shelf. (a) Image acquired in March 11 in 2011. (b) Image acquired in March 16 in 2011. (c) Ground truth image.

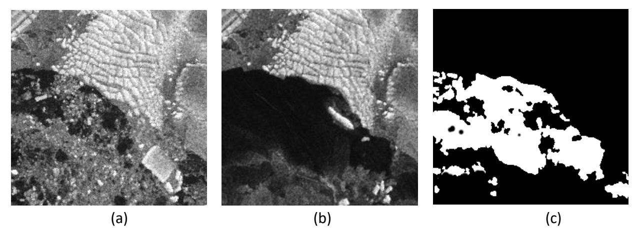


Fig. 3. Dataset II from Sulzberger Ice shelf. (a) Image acquired in March 11 in 2011. (b) Image acquired in March 16 in 2011. (c) Ground truth image.

B. Results on the Dataset I

We compare our method with two closely related methods: PCAKM [13] and GaborPCANet [14]. The final change detection maps are shown in figure form and the criteria are shown in tabular form.

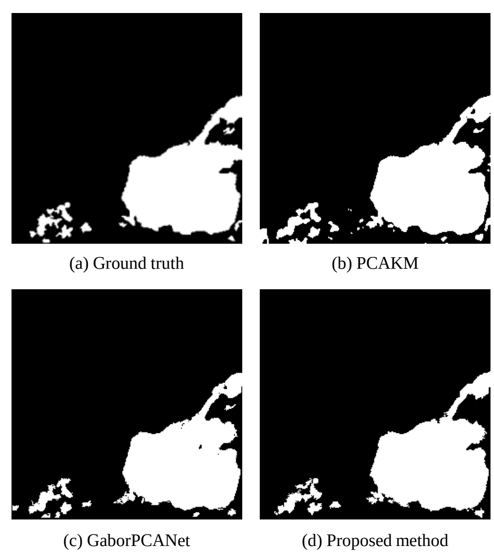


Fig. 4. Visualized results of change detection methods on Dataset I. (a) Result by PCAKM [13]. (b) Result by GaborPCANet [14]. (c) Result by the proposed method.

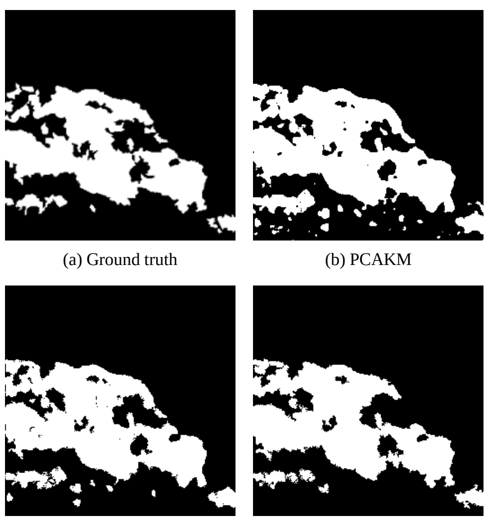
Fig. 4 shows the final change maps of different methods on Dataset I, and Table I lists the specific values for evaluation

TABLE I
CHANGE DETECTION RESULTS ON SEA ICE DATASET I.

Methods	FP	FN	OE	PCC (%)	KC(%)
PCAKM [13]	711	479	1190	98.18	94.23
GaborPCANet [14]	422	724	1146	98.25	94.35
Proposed method	429	464	893	98.64	94.65

criteria. We can observe that there are some noisy white spots in the results generated by PCAKM. Therefore, the FP value of PCAKM is relatively high. As shown in Fig. 4(c), some important changed regions are missed by GaborPCANet, and the FN value of GaborPCANet is relatively high. As shown in Fig. 4(d), the proposed method can suppress the speckle noise to some extent, and then can draw a balance between FP and FN values. The OE and PCC values of the proposed method achieves the best performance on this dataset. It proves that the proposed method can obtain satisfactory results and can effectively suppress the multiplicative speckle noise involved in learning.

C. Results on the Dataset II



(a) Ground truth (b) PCAKM (c) GaborPCANet (d) Proposed method

Fig. 5. Visualized results of change detection methods on Dataset II. (a) Result by PCAKM [13]. (b) Result by GaborPCANet [14]. (c) Result by the proposed method.

TABLE II
CHANGE DETECTION RESULTS ON DATASET II.

Methods	FP	FN	OE	PCC(%)	KC(%)
PCAKM [13]	3215	141	3356	94.88	87.13
GaborPCANet [14]	2237	599	2836	95.67	88.82
Proposed method	1580	885	2465	96.24	90.10

Fig. 5 shows the change detection results on Dataset II. Evidently, the PCAKM and GaborPCANet are contaminated severely by the speckle noise, and there are many noisy white spot in the generated change maps. Therefore, the FP values of PCAKM and GaborPCANet are much higher than the proposed method. The proposed method produces fewer false alarms and it suppresses the bad effects of multiplicative speckle noise. The quantitative and qualitative comparison on the dataset has demonstrated the superiority of the proposed method.

IV. CONCLUSION

In this paper, we proposed a novel sea ice classification framework from SAR images based on SPBL. First, log-ratio is used to generate a difference image. Then, a hierarchical FCM clustering algorithm is employed for reliable samples selection. Finally, SPBL is utilized as the classifier to provide probability outputs based upon reliable samples. Experiments on two real sea ice datasets demonstrate that our method achieves better performance than the previous methods in most cases.

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