UNSUPERVISED CHANGE DETECTION IN SAR IMAGE USING GRAPH CUTS

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ABSTRACT

Abstract — **In this paper, we present an unsupervised change detection approach in temporal sets of SAR images. The change detection is represented as a task of energy minimization and the energy function is minimized using graph cuts. Neighboring pixels are taken into account in a priority sequence according to their distance from the center pixel, and the energy function is formed based on Markov Random Field (MRF) model. Graph cuts algorithm is employed for computing maximum a-posteriori (MAP) estimates of the MRF. Experiments results obtained on a SAR data set confirm the effectiveness of the proposed approach. The comparisons between graph cuts algorithm and iterated conditional modes (ICM) algorithm about the quality of change map and running time of energy minimization illustrate that graph cuts algorithm is a huge improvement over ICM.**

Keywords* —*Markov Random Field (MRF), SAR, energy minimization, Graph cuts, iterated conditional modes (ICM)

1. INTRODUCTION

Change detection is one of the most important applications of the remote sensing technology and it plays a more and more important role in a variety of fields. Synthetic aperture radar (SAR) sensors hold a strong potential for change detection studies, especially thanks to the insensitivity of SAR imagery to atmospheric conditions and cloud cover issues [4].

It's quite popular and useful to form the unsupervised SAR change detection as pixel-labeling task under a Bayesian framework, where the labels represent two opposite classes [1], [2], [3]. This problem usually is seen as a pixel-labeling problem which can be naturally represented in terms of energy minimization. Commonly, the energy function is composed of two terms: one term penalizes solutions that are inconsistent with the observed data, while the other term enforces spatial coherence. One reason for this framework so popular is that it can be justified in term of maximum a-posteriori (MAP) estimation of a Markov random field (MRF) [1], [2], [3]. Since MRFs allow expressing a complex but effective image analysis at a global scale through the local image spatial properties, the spatial-contextual information included in the neighborhood of each pixel can be modeled accurately and all the computations are restricted to a local window. Therefore, the introduction of the Markov models in a Bayesian framework has resulted in a unified framework for image processing community. Under this framework, change detection problem, one of pixel-labeling tasks, is elegantly posed as a statistical inference problem. However, the main drawback of MRF algorithms is the computational burden of the optimization schemes associated with the energy functions. Typical optimization algorithms use the greedy strategy which visit all lattice sites in a specific order and perform a local computation at each site until some convergence criteria are reached. The algorithms that were originally used, such as simulated annealing (SA) [5] or iterated conditional modes (ICM) [6], proved to be inefficient.

Over the last few years, many new efficient energy minimization approaches have been developed for pixel-labeling tasks. Graph cuts algorithm is one of the most popular and powerful approaches for MRF energy function optimization [7], [8]. The applications of graph cuts to pixel-labeling problems, such as image restoration [7], image segmentation [9], texture modeling [10], and stereo matching [7], have proven that graph cuts gives substantially more accurate results than were previously possible. In [12], experiments confirm that graph cuts algorithm is a huge improvement over ICM and SA, and the minimum obtained by graph cuts is quite close to the global minimum.

In this paper, we deal with the unsupervised change detection on SAR images in term of energy minimization under MRF framework and minimize the energy function using graph cuts algorithm. The remainder of this paper is organized as follows: Section II introduces the change detection approach based on MRF model and the energy minimization method. Section III conducts experiments on a

bidate set of SAR images. Conclusions and discussions are given in Section IV.

2. CHANGE DETECTION USING GRAPH CUTS

The proposed approach is a two-step procedure: 1) an energy function is constructed based on MRF models so that the change detection problem is formulated in terms of energy minimization; 2) a graph based upon the image is built in which each cut defines a configuration and the minimum cost cut separating the source from the sink is found in this graph. In the first step, we define the unsupervised SAR image change detection as a binary pixel-labeling problem by assigning each pixel in log-ratio image a label changed or unchanged. Under MRF models framework, spatial-contextual information included in the neighborhood of each pixel in original SAR images is modeled elegantly and the energy function is defined as the log likelihood of the posterior distribution of a MRF. In the second step, a two node MRF is represented by the constructed graph. Each pixel in the image generates a corresponding graph vertex and two additional vertices, the source and sink, are formed to represent the changed and the unchanged part respectively. The individual unary and pairwise terms of the energy function are represented by weighted edges in the graph. Standard methods based upon max flow will find an optimal cut separating the source from the sink.

2.1. Energy Model

Let us consider two georeferenced and coregistered SAR intensity images $X_1=\{ X_1(i, j), 1 \leqslant i \leqslant I, 1 \leqslant j \leqslant J\}$ and $X_2=\{ X_2(i, j), 1 \leqslant i \leqslant I, 1 \leqslant j \leqslant J\}$ acquired over the same geographical area but at two different time *t1* and *t2*, respectively. Our aim is to generate a change detection map that represents changes that occurred on the ground between the acquisition dates. The log-ratio detector is well-known and widely used in SAR imagery due to its ability to greatly reduce the speckle influence on the change map. Therefore, the change detection problem can be viewed as pixel-labeling problem where each pixel in the log-ratio image, $X_R=\{ x_R(i, j), 1 \leqslant i \leqslant I, 1 \leqslant j \leqslant J\}$, is mapped into the set $\Omega = \{\omega_U, \omega_C\}$ of possible labels within the Bayesian theory framework. In order to analyze the log-ratio image on the basis of the Bayes theory, the main problem to be solved is the representing this pixel-labeling task in terms of energy minimization and choosing the proper approach to minimize this energy function.

MRF has long been recognized as an accurate model to represent the local statistical dependence of images. Let's consider two sets of random variables, $X_R=\{ 0<x_R(i, j)<L-1, 1 \leqslant i \leqslant I, 1 \leqslant j \leqslant J\}$ and $Y=\{y(i, j) \in \{ \omega_U, \omega_C\} \}$ corresponding respectively to the log-ratio image with L possible gray levels and the desired change detection map. $N(i, j) = \{(i, j)+ (g, h) \mid (g, h) \in N\}$, is a second-order spatial neighborhood system. The change detection problem can thus be solved by finding the least energy configuration of the MRF. The energy corresponding to a configuration y is composed by a likelihood term and a prior term as:

$$P(Y(i,j) \mid X_R(i,j),(i,j) \in N(g,h)) = \frac{1}{Z}\exp[-U(X_R)/T] \quad (1)$$

Where, U is the energy function, Z is a normalizing factor, and T is a constant. The maximization of (1) is equivalent to the minimization of $U(X_R)$, which is given by:

$$U(X_R)=E_{data}(Y_{mn},X_{mn})+\lambda E_{sm}(Y_{mn}) \quad (2)$$

Under the Markovian framework, the total energy function $U(\bullet)$ can be rewritten in terms of the local energy function. Where $E_{data}(Y_{mn},X_{mn})$ represents the correlation of intensity levels between the individual pixel Y(m, n) in final change map and the pixel X(m, n) in difference image, and $E_{sm}(Y_{mn})$ describes the potential function of the interactions among pixels in the appropriate neighborhoods. λ is the smooth weight. The details of $E_{data}(Y_{mn},M_{mn})$ and $E_{sm}(Y_{mn})$ are expressed in the follow relationship:

$$E_{data}(Y_{mn},X_{mn})=\frac{1}{2\sigma^2}\sum_{r\in N}\theta_r(x(i,j)-x_r)^2+\frac{1}{2}\log(\sigma^2) \quad (3)$$

Where, x_r is the pixels in the specified second-order spatial neighborhood system. θ_r is the spatially varying per-pairing weights.

$$E_{sm}(Y_{mn}) = \sum_{(g,h)\in Y(m,n)} \delta_k(Y(m,n),Y(g,h)) \quad (4)$$

Where $\{g, h\}$ represents the clique types, associated with the second-order spatial neighborhood system. $\delta_k(\bullet)$ is the indicator function, and is defined as:

$$\delta(y_{mn}, y_{gh}) = \begin{cases} r(y_{mn},y_{gh}), & if\ y_{mn} \neq y_{gh} \\ 0, & otherwise \end{cases} \quad (5)$$

Where $r(y_{mn},y_{gh})$ is a contrast term, favoring pixels with similar gray values having the same label.

$$r(y_{mn}, y_{gh}) = \exp\left(-\frac{(y(m,n)-y(g,h))^2}{2\sigma^2}\right) * \frac{1}{\sqrt{(m-g)^2+(n-h)^2}} \quad (6)$$

2.2. Energy Minimization Algorithms

The change detection problem expressed on MRFs can be solved by finding the least energy configuration of the MRF. The configuration x_R having the least energy corresponds to the MAP solution of the MRF. The minimization of energies defined in (2) can be performed by optimization algorithms such as graph cuts [7] and iterated conditional modes (ICM) [6]. In fact, [8] proved that an exact MAP solution of the energy function can be computed for a pairwise MRF with convex terms by finding the st-mincut.

2.2.1. Graph cuts

The graph cuts theory provides us with a powerful method to compute the globally optimal value of an energy function constructed on an edge capacitated graph *G(V,E)*. The graph-cut algorithm begins by building a graph based upon the image. Each pixel *p(i, j)* in the image generates a corresponding graph vertex *v(i, j)* . Two additional vertices form the source and sink, representing the changed and the unchanged part respectively. A typical vertex in the graph links to some nodes: the source and the sink, plus the vertices of its neighbors. The edge weight *c(u,v)* is assigned according to some measure of similarity between the two pixels. Once constructed, standard methods based upon graph flow will find an optimal cut separating the source from the sink, by which we can find the MAP-solution of the MRF.

There are two most popular graph cuts algorithms, called the α-β swap algorithm and the α-expansion algorithm [7]. Both algorithms work by dynamically updated the global minimum of a binary labeling problem after each iteration. This process converges rapidly and results in a strong local minimum, in the sense that no “permitted move” will produce a labeling with lower energy [12]. As the details of the algorithms are quite different for the swap move and the expansion move algorithms, we describe in the following sections.

For an input X_R and a pair of labels α, β, the α-β swap algorithm is to decide whether a pixel x_R is to be labeled as α or β. Therefore, α-β swap means some subset of the pixels currently given the label α can be assigned the label β, and vice verse. Starting with an arbitrary labeling L, the α-β swap algorithm goes to a local minimum for each pair of labels (α, β) in some order until no swap move can produce a lower energy labeling than the current labeling. In contrast, the α-expansion algorithm just evaluates labeling a pixel x_R as α whether reducing the energy or not. Starting with an arbitrary labeling L, the α-expansion algorithm finds a local minimum for any label α until no expansion move to produce a lower energy.

The main computational cost of graph cuts lies in computing the minimum cut, which is done via max flow. Our implementation of graph cuts uses the max flow algorithm of in [11]. Experiments illustrate that α-expansion and α-β swap algorithms have nearly the same performance, and α-expansion algorithm is a little efficient than α-β swap algorithm. Therefore, we choose α-expansion algorithm in this paper.

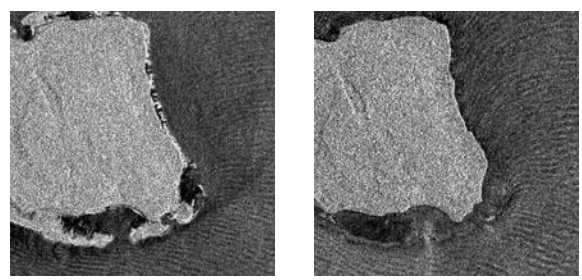
2.2.2. Iterated conditional modes (ICM)

Since it is difficult to maximize the joint probability of an MRF, Besag [6] proposed a deterministic algorithm called iterated conditional modes (ICM) which maximizes local conditional probabilities sequentially. The ICM algorithm which ignores the large-scale deficiencies of the a priori probability for a true image is a computationally feasible alterative in computing the maximum a posteriori probability (MAP) for the actual image given the observations. The ICM algorithm uses the ``greedy" strategy in the iterative local maximization. It starts with an initial estimate of the labeling, and sequentially updates each pixel by choosing the label giving the largest decrease of the energy function. This process is repeated until convergence criteria are reached. The convergence is guaranteed for the serial updating and is rapid.

Unfortunately, the result obtained by ICM depends very much on the initial estimator and is inclined to be stuck in very local minima (fairly high energy), as widely reported. Currently, it is not known how to set the initialization properly to obtain a good solution. A natural choice for is the maximum likelihood estimate. In our experiment, the ICM is initialized with the kmeans clustering.

3. EXPERIMENTAL RESULTS

In order to testify the validity of the proposed approach, we carry out an experiment on a couple of 207×207 pixels Envisat SAR images. The original images shown in figure 1 (a) and (b) were acquired over the North Sentinel Island (India) on 3 June and on 30 December 2004, before and after the Indian Ocean tsunami in 2004. The coastal destruction is evident in the December image.



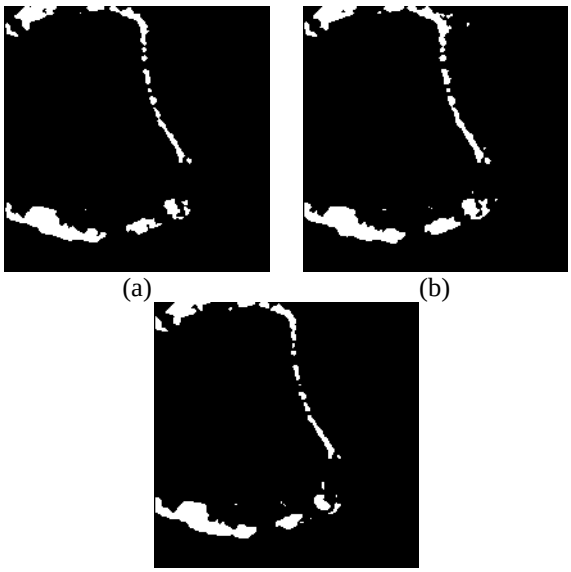
(a)Experiment image X_1 (b) Experiment image X_2

Figure 1. Envisat SAR images related to the North Sentinel island (India). (a) 3 June, 2004; (b) 30 December, 2004.

Before running the proposed approach, two parameters are necessary to be set. One is the smooth weight λ introduced in (2). We carried out experiments varying the value of this parameter from 1 to 100, and we find that $\lambda = 10$ was a robust value. The second parameter is the spatially varying per-pairing weight θ_r, which was set to a value of 1. The statistical parameters σ for changed and unchanged class were estimated by k-means clustering.

We also compare our approach with the traditional iterated conditional modes (ICM) algorithm. For the images in figure 1, using a program written in the C++ language, 13.54ms and 32.01ms were required for our approach and ICM algorithm respectively to minimize the same energy function. Figure 2 shows the change maps produced by the proposed approach and ICM algorithm described above.

Using the proposed approach, a Kappa value of 0.8897 is obtained with an overall accuracy of 98.97%, while the Kappa coefficient is 0.8525 and the overall accuracy is 98.48% by ICM algorithm. Ground truth showing in Fig. 2(c) is obtained by Manual Trial-and-Error thresholding Procedure (MTEP). All experiments were performed using the computer with Intel Pentium processor 2.80-GHz and EMS memory of 512 MB.



(a) (b)

(c)

(a)the proposed approach; (b) ICM algorithm; (c) ground truth

Figure 2. The change maps produced by the proposed approach and ICM algorithm respectively.

The reasons of the effectiveness of the proposed approach may be those: 1) MRF is an accurate model to describe a variety of image characteristics, and the statistical correlation of intensity levels among neighboring pixels is exploited in a priority sequence; 2) the global minimum is obtained by the graph cuts; 3) change map produced by our proposed approach does not depend on initialization practically.

4. CONCLUSION AND DISCUSSION

In this paper, we present an unsupervised change detection approach in temporal sets of SAR images using graph cuts. The change detection is represented in terms of energy minimization under MRFs framework, and the energy function is minimized using graph cuts. The proposed approach is capable of exploiting the spatial-contextual information in images but also overcome the computational burden of traditional algorithm. Experiments results obtained on a SAR data set confirm the effectiveness of the proposed approach. It is also proven that graph cuts algorithm is a huge improvement over ICM and SA, and the minimum obtained by graph cuts is quite close to the global minimum.

Future lines of research may be related to: 1) more sophisticated model is adopted; 2) Other minimization approaches, loopy belief propagation (LBP), message passing, can be compared.

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