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A Graph-Based Image Segmentation Approach for Image Classification and Its Application on SAR Images

Abstract*. In this paper, we propose a novel approach for image classification based on Graph-based image segmentation method and apply it on SAR images with satisfactory clustering performance and low computational cost. In this method first, the image pre-processes by mean shift algorithm to cluster into disjoint region, then the segmented regions are represented as a graph structure with all connected neighbourhood, and after that normalized cut method is applied to classify image into defined classes.*

Streszczenie. *W artykule przedstawiono metodę klasyfikacji obrazów, z wykorzystaniem segmentacji metodą grafową. Proponowana rozwiązanie wykorzystano w analizie obrazów SAR (ang. Specific Absorption Rate), uzyskując dobrą skuteczność i niski koszt obliczeniowy. (**Segmentacja metodą grafową w klasyfikacji obrazów w zastosowaniu do obrazów SAR**).*

Keywords: Polarimetric synthetic aperture radar, SAR image Classification, Graph Partitioning, Mean-Shift, Normalized Cut.
Słowa kluczowe: Polarymetryczny radar z syntezą apertury, klasyfikacja obrazów SAR, podział grafu, przesunięcie średniej, cięcie znormalizowane.

1. Introduction

The aim of image classification process is to categorize all pixels in a digital image into one of several land cover classes.

Polarimetric synthetic aperture radar (PolSAR) data or known as SAR data are complex multidimensional image data, which can be analyzed adopting several processing schemes. Synthetic aperture radar (SAR) images provide useful information for many applications, such as reconnaissance, surveillance, and targeting [1]. Many researches has been done for SAR imaging since it was found that it is unaffected by seasonal variations and weather conditions.

Classification of SAR images is a fundamental process to identify different land classes. There are different properties for different kind of land classes based on which they may be identified and hence classified, e.g., water, agricultural area, urban area, forest etc. All these classes can be identified according to their spectral properties, which vary with the imagery system, i.e., the spectral properties for aerial photograph are different than thermal image, which are again different in microwave imagery.

There are many methods and algorithms which have been applied for polarimetric SAR image classification which can be divided into three main categories: (1) classification based on physical scattering mechanisms inherent in data [8,23] (2) classification based on statistical characteristics of data [2,19] and (3) classification based on image processing techniques [13,20]. Also, there has been several works using some combinations of the above classification approaches [2, 8].

Approaches to the polarimetric SAR classification problem can also be based on supervised or unsupervised methods; their performance and suitability usually are different and depend on applications and the availability of ground truth. The supervised methods usually achieve higher classification accuracy compared to the unsupervised methods. On the other hand because of their requirements to availability and selection of training sets for each class for classifier learning, for larger datasets and large number of classes it becomes costly and time consuming for selecting appropriate training areas.

On the other hand, unsupervised methods perform classification automatically by exploiting information contained within multi-dimensional data, without investigating any training.

Here we present some recent and related works. Among the methods and works for SAR image classification, V. akbari et al. at [24] using a K-Wishart markov random field model for classification of polarimetric SAR images. J. J. Yin et al in [25] introduced a new method by using the optimization of polarimetric contrast enhancement for this approach. D. Zhang et al at [26] presented a new classifier for polarimetric SAR images based artificial neural networks. S. Uhlmann et al in [27] for Polarimetric SAR images classification used collective network of binary classifiers.

Among these supervised and unsupervised methods which mentioned above, we introduce a new and novel unsupervised method for classification of SAR images based on graph partitioning that will discuss more in detail in the next sections as the following organization: First, in section 2 the procedure of mean shift algorithm for image clustering and also spectral graph partitioning for image segmentation is described. Second, in section 3 our new approach for image classification based on graph partitioning is introduced and next in section 4 the experimental result of our method and comparison with some other methods is presented. Finally in last section the conclusion of whole work is presented.

2. Mean Shift Algorithm and Graph Partitioning

2.1. Image Clustering Based On Mean Shift Algorithm

Mean shift is a kind of clustering algorithm base on working in feature space. Here we present a brief review of image segmentation method based on mean shift algorithm [28], [29], [30] .First, image converted into feature space with a nonparametric method-kernel density estimation to model the features. Then image segmentation problem can be considered as a clustering problem by finding the modes of density function and assigning point to the modes. For example for defining kernel density estimation at point x in a dataset $\{x_i\}_{i=1}^{n} =\subset R^D$:

$$\hat{f} = \frac{1}{n}\sum_{i=1}^{n} K_H(x - x_i) \tag{1}$$

where D is the dimensionality of the data. For simplicity, we just assume the kernel widths are the same.Now the kernel density estimation becomes:

(2) $$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n} k\left(\left\|\frac{x - x_i}{h}\right\|\right)^2$$

The mean shift vector is given by:

(3) $$m(x) = \frac{\sum_{i=1}^{n} x_i k\left(\left\|\frac{x - x_i}{h}\right\|\right)^2}{\sum_{i=1}^{n} k\left(\left\|\frac{x - x_i}{h}\right\|\right)^2} - x$$

Now we iterate $x^{\tau+1} = m(x^{\tau})$ .For each point, the scheme converges to a mode of the density function (3).

Then for every point which converges to the same mode, we assign them to a cluster. Thus we get the final segmented image.

2.2. Spectral Graph Partitioning

There are many graph theoretic algorithms for partitioning problem. Among these, spectral graph partitioning methods have been successfully applied to many areas in computer vision, including motion analysis [31], image segmentation [32], [33], [34], [35], image retrieval [36], video summarization [37], and object recognition [38].In this article, we used one of spectral partitioning methods named Normalized cut (Ncut) [33] for our approach. Here we have a short review of the Ncut method based on the studies in [33], [34], and [39].

In summary, graph partitioning methods attempt to form graph nodes into groups with high similarity for intragroup and low similarity for intergroup. Given a graph $G = (V, E, W)$, where V is the set of nodes, and E is the set of edges connecting the nodes. Pair of nodes u and v is connected by an edge e and is weighted by $w(u,v) = w(v,u) \geq 0$ to measure the dissimilarity between them.

W is an edge affinity matrix with $w(u,v)$ as its (u,v) th element. The graph can be partitioned into two disjoint graphs A and $B = V - A$ by removing any edges that connect nodes in A with nodes in B . The degree of dissimilarity between the two sets can be computed as a total weight of the removed edges as:

(4) $$cut(A,B) = \sum_{u \in A,, v \in B} w(u,v)$$

The minimum cut is an algorithm to minimize the cut value. There are many methods for finding minimum cut as has been studied well in [33], [34] and [40]. However, minimum cut always try to cutting small set of isolated nodes because the cut defined in (3) does not have any intragroup information [33].

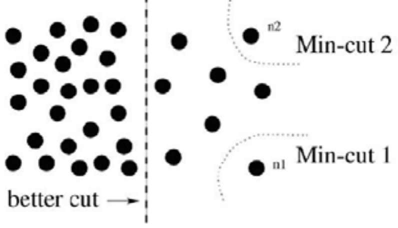

Fig.1. an example that minimum cut gives a bad partition (from [33])

So normalized cut algorithm presented for solving this problem, by considering intragroup and intergroup information as bellow formulation:

(5) $$Ncut(A,B) = \frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)}$$

Where $assoc(A,V)$ represent the total connection from nodes in A to all nodes in the graph, and $assoc(B,V)$ is similarly defined. So minimizing the disassociation between groups and maximizing the association within groups can be obtained simultaneously. Minimizing Ncut is NP-complete. So approximation methods are required. Shi at [33] presented a good approximation method for solving this problem by relating it to compute a generalized eigenvalue problem.

3. Proposed Approach

3.1 Description of Algorithm

Here we describe our proposed algorithm. The outline scheme of proposed algorithm can be categorized as the following. First, an image clustered into multiple disjoint regions using mean shift algorithm. Second, the graph representation of clustered regions is constructed which each cluster has one node, and the dissimilarity value between regions is defined. Finally, a graph partitioning algorithm based on normalized cut method is applied to obtain simultaneously the final segmentation and classification.

However, the general overview of proposed algorithm scheme that mentioned above is not the main remarkable work of this article, because it used by many researchers for image segmentation problem not for image classification approach such as J Ding at [41] and Tao W et al [42]. They used the proposed algorithm for image segmentation problem in this way that the regions produced by mean shift algorithm can be represent by a planar weighted region adjacency graph (RAG) $G = (V, E, W)$ that incorporate the topological information of the image structure and region connectivity. So the graph of clustered image forms by the RAG algorithm and connect neighboring regions node by an edge. The dissimilarity value w between neighbouring regions defines as the following. By defining the color space, we can compute the weight matrix W of all regions. The weight $w(u,v)$ between regions u and v is defined as

(6) $$w(u,v) = \begin{cases} e^{-\left[\frac{\|F(u)-F(v)\|_2^2}{d_I}\right]} & \text{If } u \text{ and } v \text{ are adjacent} \\ 0 & \text{, otherwise} \end{cases}$$

Where $F(u) = \{L(u), u(u), v(u)\}$ is the colour vector of region u and the $\|\cdot\|_2$ denotes the vector norm operator. d_I is a positive scaling factor for defining the sensitivity of $w(u,v)$ to the colour difference between nodes u and v .

By this graph representation of the image, region grouping can be formulated as a graph-partitioning problem. In [41] and [42] Ncut algorithm is used to solve this problem.but our approach has a little difference with those because it segment and classify the image simultaneously and. In next sub section we describe it in more details.

3.2. The new approach for image classification

In this section we describe more in detail about our approach in image classification based on graph based image segmentation. The process of algorithm is what is mentioned in pervious section. But the significant portion of our work that provides an approach for image classification based on graph partitioning is in the graph constructing stage. For this, after clustering image by mean shift algorithm into disjoint regions, there is one node for every region but for connecting the nodes together, we didn't follow the last method for constructing the graph. In the last method every two neighboring regions (nodes) connect with an edge based on RAG algorithm but in this method we connect all nodes together. It means that there is no adjacent restriction such (6) for calculating the measure of dissimilarity value w for every edge between nodes

(7) $$w(u,v)=e^{-\left[\frac{\|F(u)-F(v)\|_2^2}{d_I}\right]}$$

Now by defining number of classes here that was number of segmented region in last method for Ncut procedure and partitioning the weighted graph obtained by (7) by Ncut algorithm, classification of image will be achieved clearly.

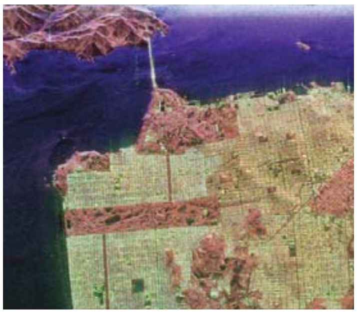

Fig.2. Original SFBay data

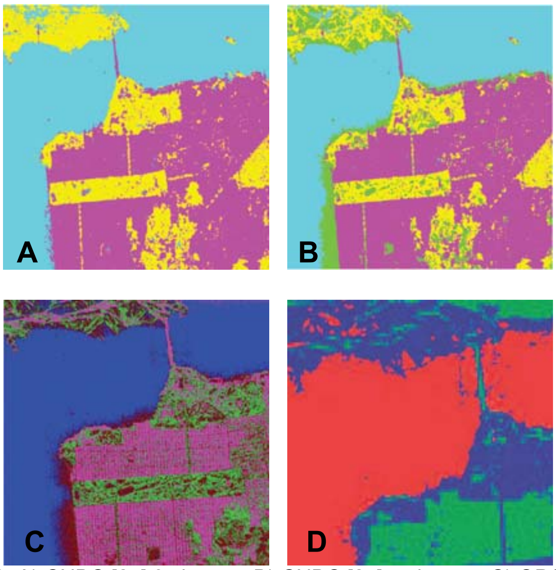

Fig.3. A) CNBC [27] 3 classes, B) CNBC [27] 4 classes, C) OPCE [25] 4 Classes, D) ANN-based [26] 3 classes.

4. Experimental Result

In this section we present the experimental result of our new method. The reason for choosing SAR images for this procedure is because there is no background or object in a SAR image which restrict our approach for image classification.

The benchmark dataset used for visual evaluation is the NASA/Jet Propulsion Laboratory Airborne SAR (AIRSAR) L-band data of the (SFBay). The original polarimetric SAR data provides good coverage of natural (sea, mountains, and forests) and man-made targets (buildings, streets, parks, roads). We defined 4 distinct classes for natural area (such as water or see, rocks or cliffs or mountains, forest or trees, urban).

Figure 3 shows classification of the sample image by other recent methods in the case of classification in 3 and 4 classes.

The result of our methods in the sample image is presented in figure 4. Here, we classify the sample image once for 3 classes and again for 4 distinct classes.

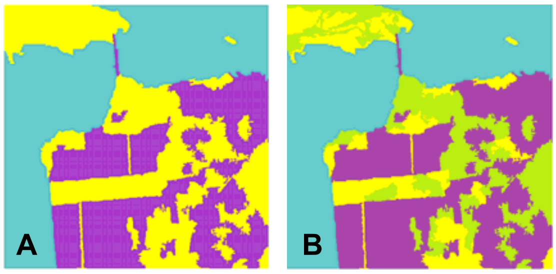

Fig.4. A) Our method 3 classes, B) Our method 4 classes

5. Conclusion

In this paper, a new approach for image classification based on graph partitioning and its application on SAR images is presented. Experimental Results was done on the goldengate San Francisco Bay SAR image and in comparison with other methods, the results show that our approach can use as a new method with high quality and low computational cost for this procedure.

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