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Synthetic Aperture Radar Remote Sensing Classification Using the Bag of Visual Words Model to Land Cover Studies

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Abstract**—**Classification of high resolution polarimetric Synthetic Aperture Radar (PolSAR) images plays an important role in land cover and land use management. Recently, classification algorithms based on Bag of Visual Words (BOVW) model have attracted significant interest among scholars and researchers in and out of the field of remote sensing. In this paper, BOVW model with pixel based low-level features has been implemented to classify a subset of San Francisco bay PolSAR image, acquired by RADARSAR 2 in C-band. We have used segment-based decision-making strategy and compared the result with the result of traditional Support Vector Machine (SVM) classifier. 90.95% overall accuracy of the classification with the proposed algorithm has shown that the proposed algorithm is comparable with the state-of-the-art methods. In addition to increase in the classification accuracy, the proposed method has decreased undesirable speckle effect of SAR images.

Keywords**—**Bag of Visual Words, classification, feature extraction, land cover management, Polarimetric Synthetic Aperture Radar.

I. Introduction

PolSAR with its unique capabilities including day-night, and all weather data acquisition system, has provided rich earth observation data and plays a vital role in land cover management. Recent developments in increasing the spatial resolution of PolSAR images create a significant opportunity to obtain more detailed information about earth surface. However, the possibility of acquiring high resolution images necessitates more powerful and robust algorithms for classification purposes [1].

Recently, classification algorithms based on BOVW representation have attracted significant interest among scholars in different fields of remote sensing including PolSAR images classification [1]-[3]. Moreover, BOVW has been applied for video processing [4], image categorization [5], and etc. with state-of-the-art results.

BOVW is originated from Bag of Words (BOW) method which has been employed on textual data for data mining. In textual data mining with BOW, a document is converted into a histogram which is a representation of repeated frequency of each word [6]. The corresponding histogram can be utilized for document categorization and subject determination.

BOVW can bridge the semantic gap between low-level features extracted from the image and high-level concept of land cover with a mid-level representation [2]. The first step in BOVW representation is low-level features extraction from raw image. Afterwards, visual words are constructed, and frequency histogram of each word through image is generated. Patch level features are used in conventional BOVW method [1]-[3] but recently, few researches have been carried out using pixel level features [7]. In this paper, BOVW model has been implemented on PolSAR data classification with pixel level local features and segment-based decision-making strategy.

II. Methodology

As mentioned in this paper, the BOVW model has been implemented to classify PolSAR image with pixel level local features. Segment based decision making strategy was used for classification. The proposed algorithm consists of three main steps as follows:

A. Low-Level Features Extraction and Image Segmentation

In the first step, different low-level features in pixel level were extracted from Polarimetric SAR image, and multiresolution segmentation algorithm is used to divide the image into 7878 segments. In [8], an optimum set of features has been suggested to classify PolSAR data with SVM classifier. In this paper, suggested optimum feature set in [8] was extracted and used as low-level feature set as well as four more low-level feature sets that are described in the experiments section. The optimum feature set of [8] is given in Table I. For a description of the symbols used in Table I, refer to [8]. For instance, [Bar]13mod represents the amplitude of the parameter in the first row and third column of the Barnes matrix [9] or [Pow]max represents the maximum of the received power [10].

B. BOVW Representation

K-means algorithm was used to cluster PolSAR image into k cluster(s) based on extracted low level features and each cluster center is considered as a visual word. Fig. 1 illustrates an example result of k-means clustering algorithm (e.g. in 2-dimension space), and each blue point (i.e. cluster centers) represents a visual word.

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By pooling the pixels of each training segment between constructed visual words, using hard voting method and Euclidean distance, each training segment would be represented by visual words' frequency histogram. Number of training and testing segments for each class is shown in Table II. At the end of this step, we calculated 207 histograms, each of which illustrates frequency of the visual words in each training segment.

C. Classification

We use the histograms, calculated in the previous step, to train the classifier. Each visual word is considered as a feature. SVM classifier with histogram intersection kernel and one against one rule to deal with multi class classification problem is used in this paper.

Fig. 2 illustrates the flowchart of main steps of the proposed algorithm.

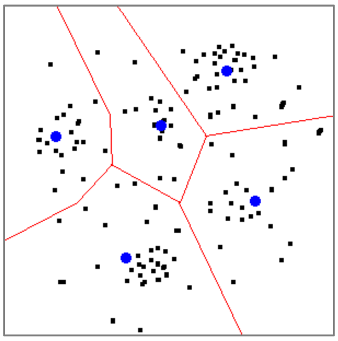

Fig. 1 The result of k-means clustering – Each blue point represents a visual word

TABLE I
SUGGESTED LOW- LEVEL FEATURES IN [8]

Selected low-level features			
A_luen	H(1-A)	HA	H_Shannon
RVI	SERD	$[T]_{12pha}$	$[Bar]_{13mod}$
$[Bar]_{13pha}$	$[Clou]_{13pha}$	$[Bar]_{22mod}$	$[Clou]_{33mod}$
$[Touzi]_{psi}$	$[Vanzyl]_{odd}$	$[krog]_{kh}$	$[Pow]_{max}$

TABLE II
NUMBER OF TRAINING AND TESTING SEGMENTS

Class Label	Training	Testing
Developed urban area	25	100
High density urban area	40	60
Low density urban area	44	67
Vegetation	54	83
Water	44	67

III. EXPERIMENTS

We have used a subset of San Francisco bay fully PolSAR image which was acquired by RADARSAT 2 in C-band in April 2008. This image is one of the mostly used images in SAR data classification over the past decade which includes both natural and man-made objects [11]. There is no available ground truth data for San Francisco bay, but the ground truth data have been generated in [11] by visually inspecting radar and optical data as well as the USGS National Land Cover Dataset (NLCD) 2006. A ground truth image based on [11] has been generated and used in this paper. Conforming from [11], five main classes can be observed in the image: 1) Developed urban area 2) High density urban area 3) Low density urban area 4) Vegetation regions and 5) Water regions. In addition, the different man-made classes may also cover trees and vegetation objects but are considered as urban classes [11]. The generated ground truth image is shown in Fig. 3 (b).

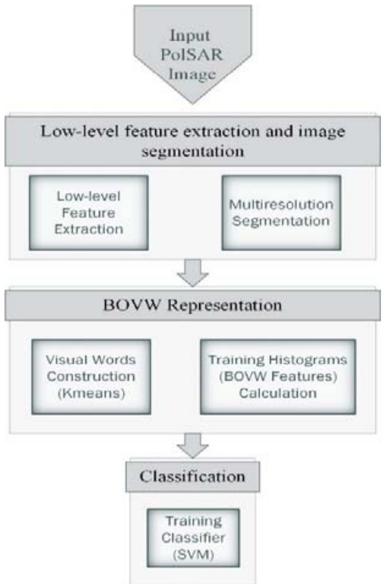

Fig. 2 Flowchart of the proposed algorithm

In order to investigate the SAR image classification performance of the proposed algorithm, we have done series of different experiments. Overall Accuracy (OA) has been chosen as the parameter to evaluate the classification performance. In addition, we have compared the result of the proposed algorithm with the result of well-known classification algorithm, SVM classifier, to better understand the BOVW mid-level representation effect on classification of PolSAR data.

Fig. 3 (a) illustrates pseudocolor composite image based on a Pauli base at an image size of 1345 × 1441 pixels. Fig. 3 (b) illustrates the generated ground truth image, and Figs. 3 (c)-(d) illustrate classification result with the proposed algorithm and traditional SVM, respectively.

A. Experiments with Different Low-Level Feature Sets

We have evaluated the classification performance of the proposed algorithm with contribution of different low-level features and the classification accuracies are given in Table III. The feature sets that we have used are: Set1: three components of the Krogager decomposition [12], Set2: Seven components of the Cloude-Pottier decomposition [13], Set3: Three components of the Freeman-Durden decomposition [14], Set4: Six parameters suggested in [15] and Set5: 16

parameters suggested in [8]. The highest OA was obtained using 16 parameters suggested in [8]. As a result, the following experiments have been done using set5 low-level features.

B. Experiments with Different Visual Vocabulary Size

Since the frequency of the visual words is the features that we have used to discriminate between different classes, visual vocabulary size can greatly affect the classification performance. We have evaluated the classification performance of the proposed algorithm with different visual vocabulary size. The obtained OAs are given is Fig. 4. As it is illustrated in Fig. 4, overall accuracy of the classification has fluctuated with changing the visual vocabulary size. The highest overall accuracy is obtained with 100 visual vocabulary size.

C. Speckle Effect

Speckle is one of the most challenging phenomena in SAR image classification. Due to the unpredictability of speckle in SAR images, dealing with its effects is difficult. As it can be seen in the classified image with traditional SVM, shown in Fig. 3 (d), speckle effect has caused noise-like classified pixels especially in water regions. But, the proposed method as a result of its segment-based decision-making strategy, has decreased the effect of speckle and improved the uniformity of the classified image. Classified image with the proposed algorithm is shown in Fig. 3 (c).

D. Comparison with Traditional SVM

In order to compare the proposed algorithm with well-known SVM classifier, we have implemented traditional SVM with set5 features and one against one rule to deal with multiclass classification problem. The result is illustrated in Fig. 3 (d). As it is shown in Fig. 3 (d), undesirable effect of speckle can be seen in the classification result of traditional SVM, whereas the classification result of the proposed algorithm, illustrated in Fig. 3 (c), provided uniform and cogent classified image. Fig. 5 illustrates the comparison of classification accuracies of the proposed algorithm and traditional SVM. The proposed algorithm has led to much higher classification accuracies.

TABLE III
PROPOSED ALGORITHM'S CLASSIFICATION ACCURACIES WITH DIFFERENT LOW-LEVEL FEATURE SETS

Class Label	Set1	Set2	Set3	Set4	Set5
Developed urban area	74%	75%	61%	66%	74%
High density urban area	83.33%	86.67%	95%	100%	96.67%
Low density urban area	74.63%	88.06%	92.54%	91.04%	97.01%
Vegetation region	93.98%	80.72%	100%	95.18%	91.56%
Water region	95.52%	95.52%	95.52%	95.52%	95.52%
Overall accuracy	84.29%	85.19%	88.81%	89.55%	90.95%

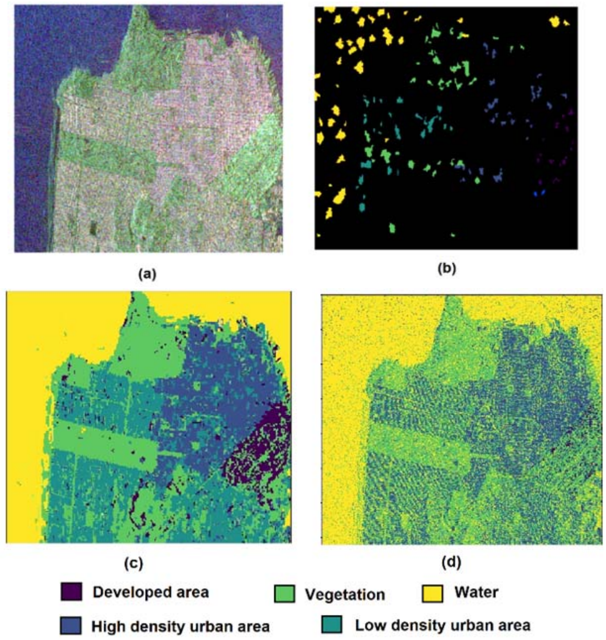

Fig. 3 (a) Pseudocolor composite image based on a Pauli base of experimental subset, (b) ground truth image, (c) classification result of the proposed algorithm, (d) classification result of traditional SVM

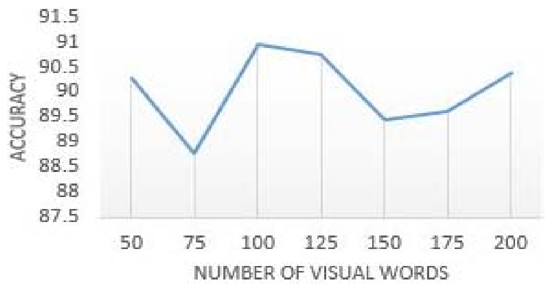

Fig. 4 Classification accuracies of the proposed algorithm with different visual vocabulary size

Fig. 5 Classification accuracies of BOVW-SVM and traditional SVM

IV. CONCLUSION

In this paper, the BOVW model has been evaluated with pixel level features and segment-based decision-making strategy to classify PolSAR image. The simple and popular clustering algorithm, K-means, has been used to construct visual words and well-known SVM has been used as the classifier. Satisfactory classification accuracies and images have shown the suitability of the proposed BOVW model for PolSAR data classification and have proved the superiority of the proposed algorithm over traditional SVM. As well as higher classification accuracies, the proposed algorithm has reduced undesirable effect of speckle, which unpredictably exists in PolSAR images, and provided uniform classification image.

Despite satisfactory results, there are still possibilities to improve classification result and accuracy that require additional research. Low-level features suggested in [8] are not optimized to be used in BOVW model and particularly optimized low-level feature sets might provide better results. In addition, more detailed ground truth data must be used to validate the classification result.

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