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Research paper

Denoising and SAR Image Classification with K-SVD Algorithm

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Abstract

Synthetic Aperture Radar (SAR) is not only having the characteristic of obtaining images during all-day, all-weather, but also provides object information which is distinctive from visible and infrared sensors. but, SAR images have more speckles noise and fewer bands. This paper propose a method for denoising, feature extraction and classification of SAR images. Initially the image was denoised using K-Singular Value Decomposition (K-SVD) algorithm. Then the Gray Level Histogram (GLH) and Gray Level Co-occurrence Matrix (GLCM) are used for extraction of features. Secondly, the extracted feature vectors from the first step were combined using the correlation analysis to decrease the dimensionality of the feature spaces. Thirdly, Classification of SAR images was done in Sparse Representations Classification (SRC) and Support Vector Machines (SVMs). The results indicate that the performance of the introduce SAR classification method is good. The above mentioned classifications techniques are enhanced and performance parameters are computed using MATLAB 2014a software.

Keywords: *Image classification, Multisize Patches, Sparse Representation-based on classification (SRC), K-SVD, Synthetic Aperture Radar Image*

1. Introduction

Classification of synthetic Aperture Radar (SAR) Images is a most important for identification of urban and rural areas, vegetation lands, buildings, lakes and any interesting object etc. Region specification is a necessary step towards automated classification of SAR images. The blurring due to some stern conditions and unexpected disturbances, it will become most challenging for target recognition [1]. The two basic approaches have been found in the literature for image classification; pixel and Object based classifications. In the pixel based classification, a group of identical pixels are called as image objects. The aim of the pixel based image classification is to assign each pixel of the image to a class with regard to a feature space. These features can be essential properties of images such as intensity or amplitude [2]. However, SAR images are surely merged by speckle noise, which will decrease the image quality seriously. Which is the information or features obtained depend on the pixel values without denosing the images for removing the speckle noise for classification are not suitable.

In the recent decades, many algorithms are proposed to discarding the speckle noise; substantive traditional methods are Lee filter [18], Frost filter [19], Kuan filter [20] and wavelet [4, 5], and so on. Image denoising (in addition to SAR image De speckling) depend on sparse representation became a current research hotspot newly [6].

A. Sparse representation of image

Compared with conventional techniques, this technique can yield better de speckle effect and image fidelity. The image can be fragmented in to an over-complete dictionary, and then one can obtained the sparse image and more details of this sparse representation are given below.

We frequently fragmented the signal with Fourier Transform, Shot-Time Fourier Transform, and Wavelet Transforms. Decomposition of the signal is generally expressed as[1]

$$f_s = \sum_{k=1}^{N} c_k \, p_k \qquad (1)$$

In the expression, f_s is the signal to be decomposed, p_k is basis function, and c_k is decomposition coefficient. This decomposition is depending on a complete orthogonal basis, which has some defects (noise, energy, weighted and corrupted signals these are few defects) on detailed description of the signal.

So researchers were focused in fragmentation the signal on an over-complete dictionary. The dictionary contains elements. Each element is also called as atom. The over-complete dictionary gives redundant information of signal .This signal called sparse signal. Enlarge the theory to the two-dimensional image, sparse fragmentation of the signal is selecting the linear combination of the optimal atom form, the over-complete dictionary to indicate an image. It represents the testing samples in an over complete dictionary in which the atoms are the training samples. If each class in training samples has sufficient atoms, it can represent the testing sample as a linear combination of the training samples.

In sparse representation classification (SRC); the sparse coefficients associated with the different classes are selected to reconstruct the original signal. Then, the residual between the original and the reconstruction signal is defined as a criterion, and the final result will be determined with the minimum residual.

B. Feature Extraction

In fact, SRC cannot be enforced to SAR image classification directly due to the imaging operation being different from that of general imagery. However, if a SAR image is converted into a particular feature space, SRC can be precisely used in SAR images [3], [4]. In this paper, we utilize a gray-level histogram [13] and a gray-level co-occurrence matrix (GLCM) [13] to get the features of a SAR image. Gray-level histogram is stable in the existence of noise and over change in view and can be used to distinguish and characterize the objects.

Therefore, it can extract an effective distribution feature from the SAR image and be applied in a large amount of classification tasks. GLCM is also used to represent SAR image texture, and we utilize a range of different size patches to adequately capture both micro textures and macro textures in the original SAR image. Thus, a particular feature vector is collected of the gray-level histogram and GLCM.

C.SRC (Sparse Representation Classification)

SRC represents the samples from a single class that lies in a linear subspace. Assume that K classes are known, e.g., we can specify a dictionary established by adding feature vectors of those classes. The testing sample y can be formulated by a array of training samples as follows [3].

$$y = D\psi_0 \epsilon R^m \tag{2}$$

Here $\psi_0 = [0, , \ldots 0, \varphi_{i,1}, \varphi_{i,2}, \varphi_{i,n_i}, 0 \ldots, 0]^T \epsilon R^n$ a coefficient vector is whose opens are zeros except those related with the i^{th} class. The coefficient of the sparser ψ_0 is easier it can identity and estimate of the sampling test of y. This is necessary to discover the sparsest solution to satisfy this equation is $y = D\psi_0$.It is mainly based on the aforementioned analysis the problem about SRC can be modeled as

$$\hat{\psi}_0 = arg\ min\|\psi\|_0 \quad subject\ to\ D\psi = y \tag{3}$$

Where$\|\cdot\|_0$ denote the ℓ^0 norm. Depending on the development in sparse representation and flatten sensing, it has been proved that if the solution ψ_0 is sparse sufficient, the solution to ℓ^0-minimization problem equals to the solution to ℓ^1minimization one, which can be relaxed as

$$\hat{\psi}_1 = \arg\ min\,\|\psi\|_1\ subjecttoD\psi = y \tag{4}$$

Let $\delta_i: R^n \rightarrow R^n$ be the characteristic function for each class. The coefficient vector is $\psi \epsilon R^n, \delta_i(\psi)$ is new coefficient vector in which nonzero, it can get a linear reconstruction $\hat{y}_i = D\delta_i(\hat{\psi})$ to approximate the testing sample y [11].We can classify y in accordance with the minimization of residual between y and $\hat{y}$ as follows: $min_i\ r_i\ (y) = \|y - D\delta_i(\hat{\psi})\|_2$

In according to we obtained the sparse coefficients, employ the orthogonal matching pursuit (OMP) algorithm to solve the sparsity constrained optimization problem in (3). In the paper we considered the Orthogonal Matching Pursuit (OMP) Algorithm for the recollecting of the support of the Sparse Signal. OMP is an repetitive Algorithm that selects at each step the column of which is most related coefficients with the present residuals. This column is then added into the set of selected columns. The algorithms updates the residuals by launching the inspection on to the linear subspace covered by the columns that have already selected and the algorithm then repeat a big benefit of the OMP is its absence of complication and speed implementation. This method has been used for recovery of signal and approximation. In this paper OMP algorithm used for noise removal.

In this paper remove noise that is De speckle noise of SAR images by using K-SVD (K-Singular Value Decomposition) algorithm, here K means clustering and the Research work is standardized as follows in the section 2 which manage with the methodology of SAR image denoising and also discussed about classification the techniques. In the Section 3 we explains the experimental results of denoising and classification accuracy using SVM. The multiple patches of different sizes help us to increase the quality of the SAR images. We also distinguished classification accuracies of denoising techniques. In section 4 discussed about the conclusion.

2. SAR image Denoising and classification techniques

The framework of our method is shown in Fig. 1. In this section, we will introduce the proposed method in detail.

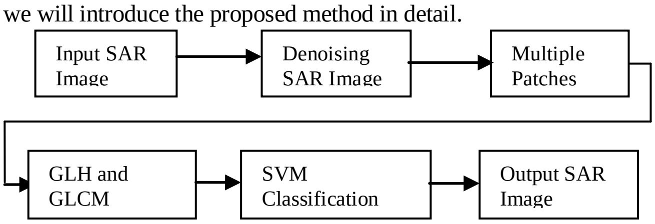


Fig. 1.Multisize patch-based SRC for SAR image classification

A. Multisize Patch-Based Dictionary

In the sparse representation application, constructing a dictionary is the first step. The dictionary in our method is not constructed directly by pixel values. To counter the complication of topography and geomorphology and aperture ambiguous appearance in the SAR image, it is necessary to transform the pixel value space into feature space, which not only decrease the calculation complexity but also selection the different features from the SAR image. In our method, feature vectors are produced by exploiting statistics properties in the gray-level histogram and utilizing texture statistics distribution in GLCM, respectively. We concatenate these two kinds of vectors to form a final feature vector for representing each pixel. This nonlinear feature will support aggregative performance by indicating statistical information and grabbing texture information in adjoining areas. We select $n_i$vectors of training samples from the i^{th}class in the h^{th} layer as columns to construct a matrix $A_i^h = [x_{i,1}^h, x_{i,2,\ldots}^h, x_{i,n_i}^h] \epsilon R^{m \times n_i}$ where m indicating the dimension of the feature vector. Then we define the dictionary D^h as the connection of the n_i training sample vectors of all K defined classes in the fixed h^{th} layer.

$$D^h = [A_1^h, A_2^h, \ldots, A_K^h] = [x_{1,1}^h, x_{1,2}^h, \ldots, x_{K,n_K}^h] \tag{5}$$

Where D^h indicating a fixed hierarchical dictionary. Let $h = \{h_1, h_{2,} \ldots h_H\}$ enumerate the H latent layers; H also means the total classification number. Extracted feature vectors from a fixed h-level patch to represent pixel points and construct a fixed-level dictionaryD_h. We can define the patch size (odd) as $S_h = \{S_1, S_2, \ldots, S_N\}, S_1 > S_2 > \cdots . > S_N, S_h$ and N is the number of patches and the size, respectively. As mentioned earlier, the number of layers is connected with the patch sizes, but they are not consistently one-to-one correspondent. The multisize patch-based method is identical to the human visual system, which always glances at the outline of the object first and then carefully observes the details. In the experiments, we only use three sizes to extract the feature of each pixel. Let PS be the resolution of the image. First, we select a size $S_{init} = 2^* floor\left({}^{PS^*3}/_2\right) + 1$ and then choose an appropriate largest odd patch size S_{large} based on different terrain types and the size of the texton in the neighborhood of S_{init}. Second, in order to capture the finer structures, we set 3×3 as the smallest patch size S_{small} and choose a middle size $S_{small} + {}^{(S_{large}-3)}/_{2} + mod(({}^{S_{large}}-3)/_{2}, 2$ to connect the classification at different layers.

B. Multiple SRC

In Multiple SRC, we use ℓ^0 minimization in (2) to describe the sparse representation problem, which can be approximately solved by a greedy pursuit algorithm. Here, the OMP algorithm is utilized to look for the support atoms and to calculate the representation coefficients. We make a judgment on the residual $r_i(y)$ to approximate the reliability of classified pixels. In another words, if $r_i(y)$ lies in a described range, we define the pixel as a reliable one; otherwise, we define the pixel as an uncertain one, and it may be determined in the next layer. The training samples in the next classification process are extracted from the labeled points in the earlier classification result. The training samples at the first layer are randomly selected in the SAR image. At the last layer, the uncertain data points will be classified by the traditional SRC.The minimum residual $r_{min}^h(y)$

$$\tau^h = r_{min}^h(y) = min_{i=1\ldots K}\, r_i^h(y) \qquad (6)$$
$$\theta^h = arg\, min_{i=1\ldots K}\, r_i^h(y)$$

Where K and θ denote the number of the class and the label with the minimum residual. To eliminate ambiguity, let τ^h represent the minimum $r_i(y)$ in the following algorithm. The label of each pixel under the residual judgment is determined as follows:

$$Label(y)^h = \begin{cases} min_i r_i^h(y), \tau^h \le \Delta_{1,} \left|r_{i \ne \theta^h}^h(y) - \tau^h\right| \ge \Delta_2 \\ uncertain, \qquad else \end{cases} \qquad (7)$$

Where $\Delta_1\, and\ \Delta_2$ represent the thresholds. The two terms of judgments convey two kinds of effective messages. The first term $\tau^h \le \Delta_1$means that the smaller the reconstruction error $r_{min}^h(y)$ is, the more similar y and class θ are, e.g., y can be effectively sparsely represented by class θ under a smaller residual. The second term $\left|r_{i\ne\theta^h}^h(y) - \tau^h\right| \ge \Delta_2$means that only the class θ can effectively represent y and other classes cannot represent y well. In other words, the two terms add a strong constraint to the inter-class distance and intra class distance, i.e., only under this condition is very similar to classθ. With the increase of h, the uncertain pixels decrease gradually. In our method, the multisize patch-based dictionary is utilized repeatedly until all dictionaries are used up .The proposed algorithm is outlined in below

Algorithm 1 Multi-size patch based multiple SRC.

1. Constructing initial dictionary (h=1): Given K classes, select n_i samples from each class randomly, each sample is indicated by a m-dimensional vector that constrict the initial dictionary $D^{init} = [A_1^{init}, A_2^{init}, \ldots, A_K^{init}]$, $init = 1$, where the feature vectors are extracted by the patch in the first layer.
2. Multiple classification $(1 \le h \le H-1)$: classify all pixels using (8) in the first layer and uncertain points in other layers. Determine which category of the testing sample y belongs to.
3. Constructing h^{th} dictionary $(2 \le h \le H)$: Select n points from each class which is labeled as new training samples in the earlier layer, and extract the feature vector $x_{i,j}^h$at h-th layer. Arrange these vectors as columns to construct the hierarchical dictionary$D^h = [A_1^h, A_2^h, \ldots\ldots, A_K^h] \in R^{m\times n}$
4. Classification at the last layer ($h = H$): Utilize the H^{th} dictionary D^H to classify the uncertain points in SAR image by traditional sparse representation classifier.

C. Dictionary training based on K-SVD

In sparse indication, adaptive dictionary explains attributes of the image is most detailed than the fixed dictionary. K-SVD is a best adaptive algorithm in training dictionary. Let$D \epsilon \mathbb{R}^{n\times k}$is a fixed over-complete dictionary, $f \epsilon \mathbb{R}^n$ is a block of noisy image, $x \epsilon \mathbb{R}^k$ is the coefficient vector of sparse representation, and$\{f_i\}_{i=1}^N, X = \{x_i\}_{i=1}^N$. The algorithm is as follows. Sparse decomposition: we use an sufficient pursuit algorithm for clarifying the following equation to get X:

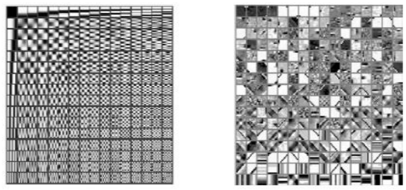


Fig.2.(a).DCT dictionary D (b) Adaptive dictionary D

D. De-noising process of SAR image

In the introduction, SAR image has surely speckle noise. This noise is distinctive from common additive noise; it is bring about by a coherent superposition of waves. Goodman suggested the concept speckle noise in 1976 [8]. based on the nature of speckle noise, multiplicative noise model of SAR image was constructed as [19, 20]:

$$f = SX \qquad (8)$$

Where, f is the intensity of the noisy image which is taken, S is a random variable of speckle noise, and X is a radar scattering properties of the target. For removal speckle noise logarithmic transformation can be used, so speckle noise is modeled as additive noise

$$f = \log(f) = \tilde{S} + X \qquad (9)$$

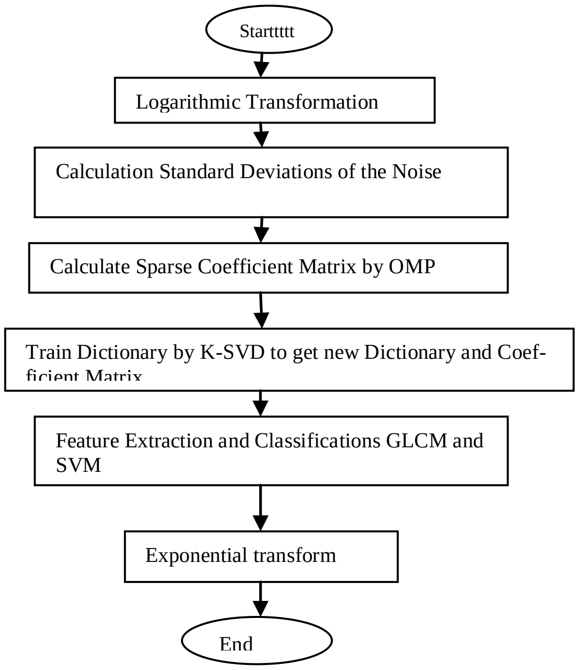
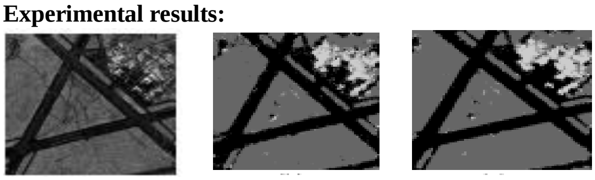


Fig.3 Flowchart of overall experiment of SAR Imagr denoising and classifications

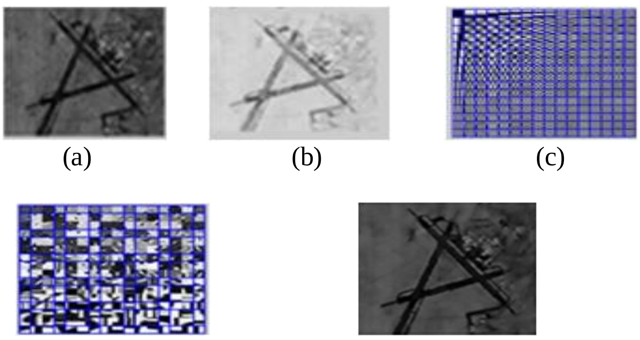
3. Discussion And Results

In fact, the noise model of SAR image was logarithmic transformed after, so we must exponential transform *X* to get the final result. The common idea of SAR image de-noising is: First, fragmentation SAR image *Y'* which was logarithmic transformed by OMP algorithm on DCT dictionary *D* to obtained the sparse coefficient matrix *a*. Second, train the dictionary *D* by K-SVD algorithm to obtained the Adaptive dictionary *D'* and updated sparse coefficient matrix *a'*. Finally, compute the result *X* of de-noising image by filtering equation, and do exponential transform to *X* to get the final result. The overall experiment represent from first to last flow diagram is shown in Figure 3.
Experiments results are in figure number 5 compared with reference figure number 4 below. These are simulations in fig 5(a) is original SAR 8x8 size image, (b) with noised image, (c) trained DCT dictionary D and (d) Multisize patches of K-SVD that is adaptive Dictionary D', (e) final SAR image classifications. The SAR image 8x8 size of the classification of the data was done with SVM with the trained data of the multiple patches, in reference size of images not only 8x8 size images but in this paper only 8x8 size SAR image is classified using multisize patches.
Accuracy = matched labels over all the classes/total labels over all the classes
Overall 97% of classification accuracy has been observed with the multiple patches over sparse representations.
Experimental results:



(a) (b) (c)

Fig.4: Reference figures [3] (a) Original Image 8x8 size (b) second level (c) final level 8x8 size image.



(a) (b) (c) (d) (e)

Fig:5.(a)Original SAR image (b) Noisy Image(c)Trained DCT Dictionary of 8x8 size image(d)Multisize patches K-SVD (e) Final filtered SAR Image

(a) (b)

Fig:6. Comparison of final SAR Denoised image (a) Input of SAR Image(b) Final Filtered SAR Image

Table-1: different noise levels of SAR image

NOISE LEVEL(SIGMA)	PSNR OF NOISE SAR IMAGE(DB)	DENOISE SAR IMAGE PSNR(DB)	RMSE
10	28.12	34.16	4.95
25	22.17	30.64	10
50	14.74	24.93	16

Here table-1 shows different noise levels added SAR image and denoised done based on PSNR values and increasing the PSNR of SAR output images. RMSE is indicated that how much difference between the original SAR image and reconstructed SAR image. Whenever noise level is low that time accurately reconstruction possible.

4.Conclusion

In the multiple patches have been trained over the image with respect to different denoising process. SAR image denoiseing over completed dictionary using KSVD adaptive dictionary better denoised than DCT dictionary. Later classification of the data was done with SVM with the trained data of the multiple patches. Overall 97% of classification accuracy has been observed with the multiple patches over sparse representations. It has been compared with respect to the previous technique the previous classification accuracy was 92%.

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