A Survey on Various Classification Methods for SAR Images

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Abstract – Synthetic Aperture Radar is the ground images captured from the satellite. These images are captured by various GPS system, region, earth or weather monitoring system to identify the particular desired location or some abnormal activity happing in some area, city or country. These are the high resolution images captured from distance in day, night or under environmental conditions. These images can be processed into different forms to identify the relative regions, image categorization etc. In this paper, an exploration of the SAR images and the associated application is provided. The paper also provided the description some of the common region and SAR image classification methods including LDA, KNN, Decision Tree and Bayesian Network. The method exploration is here provided with the process level specification.

Index Terms – SAR Images, Classification, Region Extraction, High-Resolution.

1. INTRODUCTION

SAR images are the satellite captured high resoluton images which are having higher significance in various real time applications including water region identification, forest identification etc. These images are interpreted to analyze the associated feature to identify the category of image. The region analysis can be done based on texture analysis or the statistical observation. The work model is here presented to classify the images from the pool based on content analysis. The work will be able to identify water, building, mountain etc. strengthen images accurately and effectively. To create a SAR image, successive pulses of radio waves are transmitted to "illuminate" a target scene, and the echo of each pulse is received and recorded. The pulses are transmitted and the echoes received using a single beam-forming antenna, with wavelengths of a meter down to several millimeters. As the SAR device on board the aircraft or spacecraft moves, the antenna location relative to the target changes with time. Signal processing of the successive recorded radar echoes allows the combining of the recordings from these multiple antenna positions – this process forms the 'synthetic antenna aperture', and allows the creation of higher resolution images than would otherwise be possible with a given physical antenna. SAR images have wide applications in remote sensing and mapping of the surfaces of both the Earth and other planets. SAR can also be implemented as inverse SAR by observing a moving target over a substantial time with a stationary antenna.

Applications of SAR images

- Glacier monitoring
- Sea ice mapping
- Wind movement on ocean surface
- Mapping of Antarctic
- Volcano inflation and deflation
- Urban signatures
- Land cover mapping/monitoring
- Geomorphology and ocean surface during hurricanes

SAR Image processing steps

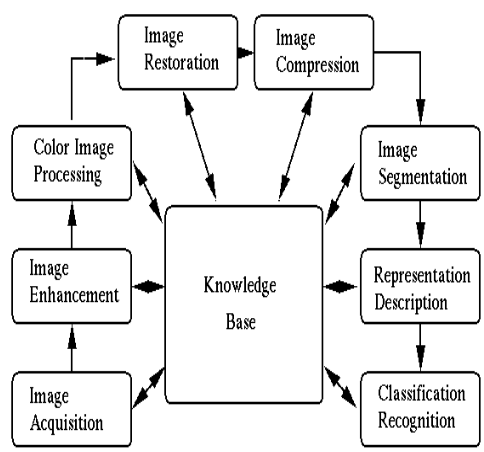


Fig. 1.: SAR Image Processing

11. Image Acquisition : This is the first step or process of the fundamental steps of digital image processing. Image acquisition could be as simple as being given an image that is already in digital form. Generally, the image acquisition stage involves preprocessing, such as scaling etc.

1.2 Image Enhancement : Image enhancement is among the simplest and most appealing areas of digital image processing. Basically, the idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interest in an image. Such as, changing brightness & contrast etc.

1.3 Image Restoration : Image restoration is an area that also deals with improving the appearance of an image. However, unlike enhancement, which is subjective, image restoration is objective, in the sense that restoration techniques tend to be based on mathematical or probabilistic models of image degradation.

1.4 Compression : Compression deals with techniques for reducing the storage required to save an image or the bandwidth to transmit it. Particularly in the uses of internet it is very much necessary to compress data.

1.5 Segmentation : Segmentation procedures partition an image into its constituent parts or objects. In general, autonomous segmentation is one of the most difficult tasks in digital image processing. A rugged segmentation procedure brings the process a long way toward successful solution of imaging problems that require objects to be identified individually.

1.6 Representation and Description : Representation and description almost always follow the output of a segmentation stage, which usually is raw pixel data, constituting either the boundary of a region or all the points in the region itself. Choosing a representation is only part of the solution for transforming raw data into a form suitable for subsequent computer processing. Description deals with extracting attributes that result in some quantitative information of interest or are basic for differentiating one class of objects from another.

1.7 Object recognition : Recognition is the process that assigns a label, such as, "vehicle" to an object based on its descriptors.

1.8 Knowledge Base : Knowledge may be as simple as detailing regions of an image where the information of interest is known to be located, thus limiting the search that has to be conducted in seeking that information. The knowledge base also can be quite complex, such as an interrelated list of all major possible defects in a materials inspection problem or an image database containing high-resolution satellite images of a region in connection with change-detection applications.

2. RELATED WORK

Jilan Feng(2014) has presented a two stage approach for texture and amplitude feature based SAR image classification. The proposed approach is based on superpixels obtained with some over-segmentation methods, and consists of two stages. In the first stage, the SAR image is classified with amplitude and texture feature used separately. Author define the CRF based on region adjacent graph (RAG) of superpixels[1]. Xiaorong Xue has defined a classification method based on polar metric and spatial features. In the method, polarimetric scattering characteristics of fully polarimetric SAR image is used, and in the denoised total power image of polarimetric SAR, Span, the texture features of gray level co–occurrence matrix are extracted at the same time. Finally, the polarimetric information and texture information are combined for fully polarimetric SAR Image classification by clustering algorithm[2]. Debabrata Samanta(2012) has presented a novel approach for SAR image classification using clustering and color space analysis. Author consider the problem of SAR image Classification by Histogram thresholding technique. Then Author proposed Color space clustering and Watershed Classification for merging different region to get the classified SAR images[3]. Jie Geng(2015) provided a work on SAR image classification using autoencoder. The feature representation based evaluation is applied to identify the difficulty region and provide the feature based modeling to overcome the associated problem. The deep network is composed of eight layers: a convolutional layer to extract texture features, a scale transformation layer to aggregate neighbor information, four layers based on sparse autoencoders to optimize features and classify, and last two layers for postprocessing[5]

Lihai Yuan(2006) has provided the EM algorithm based map image classification. Presented main work is to select a Gaussian mixture model and then use it in a MAP classification algorithm. The model is assumed that the whole distribution could be separated into finite parametric density distributions, and then the maximum likelihood parameters of each proportional distribution can be estimated by EM iterative computation[6]. V.V.Chamundeeswari(2007) provided the contour tracking to perform land cover classification. Author have presented an unsupervised classification algorithm using Maximum a posteriori (MAP) segmentation for SAR images in which SAR image is classified into monotone, texture and edge regions. Monotone and textured regions are labeled as land cover types like water, urban and vegetation areas using K-means classification[7]. Guan Dong-dong(2015) used the local pattern descriptor as the SAR image classifier. The method of image quantization is based on recent local binary pattern. For an SAR image patch in a moving window, after quantization, different patterns can be obtained, which represent the local structures that exist in SAR image[10]. Dengxin Dai(2010) used the local pattern based histogram for SAR image classification. The method describes the size distributions of bright, dark, and homogenous patterns appearing in a moving window at various contrasts; these patterns are the elementary properties of SAR image texture[12]. Lan Gao(2006) has used a fuzzy based unsupervised classification method for SAR image classification. Author employed the textural feature in SAR image to extract the transition and propose a new fuzzy unsupervised classification method for SAR images using the transition region to define the initial value and the number of cluster adaptively[16].

Shuiping Gou(2013) has used the eigen feature approach for SAR image classification. The approach consists of two parts. Initially, the statistical distributions of eigenvalue for homogeneous areas are analyzed by taking eigenvalues as the features of polarimetric information. The Bayesian classification method is applied to verify the feasibility of distinguishing different homogeneous areas[17]. Stefan Uhlmann(2013) has used the integrated features for SAR image classification. Author first review previous attempts for PolSAR classifications using various feature combinations and then Author introduce and perform in-depth investigation of the application of color features over the Pauli color-coded images besides SAR and texture features. Author then consider support vector machines and random forests classifier topologies to test and evaluate the role of color features over the classification performance[15]. Lamei Zhang(2013) has used the polar metric features and the sparse feature theory for effective SAR image classification. The method generated the features under global interest and applied the vector dictionary based error evaluation. A Simplified Matching Pursuit (SMP) algorithm is proposed to solve the optimization problem of sparse representation of PolSAR images[13].

K. S. Chen (1997) has used the filter effect based polar metric method for effective SAR image classification. The paper examined the features effects on the image classification by a supervised fuzzy dynamic learning neural network trained by a Kalman filter technique. Based on the available ground truth, the classification performance were evaluated using the original and filtered SAR images. Two independent test sites are selected for this purpose[14]. Narcisse Talla Tankam (2011) considered the structural and statistical features for SAR image classification. Author defined the suitable size of the image window used in the proposed approach of supervised image classification. This approach is based on a new way of characterising different classes identified on the image. The first step consists in determining relevant area of interest. The second step consists in characterising each area identified, by a matrix. The last step consists in automating the process for image classification[8]. Deliang Xiang(2013) used the location and intensity similarity observation for SAR image classification. Author proposed a novel superpixel generating algorithm based on pixel intensity and location similarity (PILS) for SAR image. In addition, for the sake of image classification, features of Gabor filters and gray level co-occurrence matrix (GLCM) are extracted from each superpixel. The proposed superpixel generating method has the following three characteristics: 1) the terrain boundaries of SAR image are preserved well; 2) the method has more robustness against speckle noise; and 3) it has high computational efficiency[9].

3. CLASSIFICATION APPROACHES

3.1 Support Vector Machines (SVM)

Support Vector Machines are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships. A schematic example is shown in the illustration below. In this example, the objects belong either to class GREEN or RED. The separating line defines a boundary on the right side of which all objects are GREEN and to the left of which all objects are RED. Any new object (white circle) falling to the right is labeled, i.e., classified, as GREEN (or classified as RED should it fall to the left of the separating line).

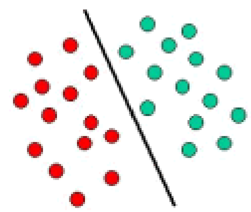


Fig. 2. Linear Classification using SVM

The above figure 2 is a classic example of a linear classifier, i.e., a classifier that separates a set of objects into their respective groups (GREEN and RED in this case) with a line. Most classification tasks, however, are not that simple, and often more complex structures are needed in order to make an optimal separation, i.e., correctly classify new objects (test cases) on the basis of the examples that are available (train cases). This situation is depicted in the illustration below. Compared to the previous schematic, it is clear that a full separation of the GREEN and RED objects would require a curve (which is more complex than a line). Classification tasks based on drawing separating lines to distinguish between objects of different class memberships are known as hyperplane classifiers. Support Vector Machines are particularly suited to handle such tasks. Here the non-linear classification process is showin in figure 3.

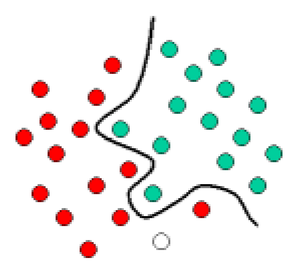


Fig. 3. Non-Linear Classification using SVM

3.2 Linear discriminant analysis (LDA)

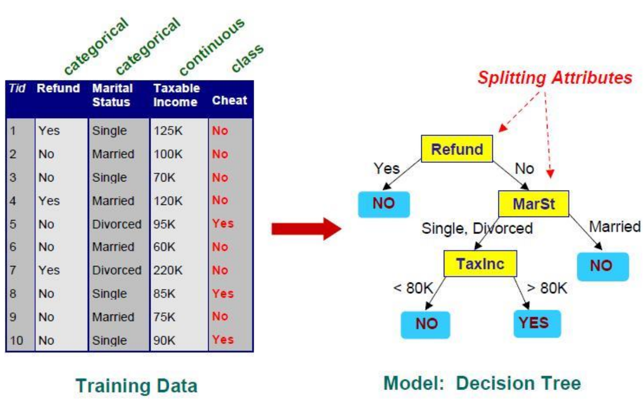
LDA is a generalization of Fisher's linear discriminant,a method used in statistics, pattern recognition and machine learning to find a linear combination of features that characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification.

LDA is closely related to analysis of variance (ANOVA) and regression analysis, which also attempt to express one dependent variable as a linear combination of other features or measurements. However, ANOVA uses categorical independent variables and a continuous dependent variable, whereas discriminant analysis has continuous independent variables and a categorical dependent variable (*i.e.* the class label).Logistic regression and probit regression are more similar to LDA than ANOVA is, as they also explain a categorical variable by the values of continuous independent variables. These other methods are preferable in applications where it is not reasonable to assume that the independent variables are normally distributed, which is a fundamental assumption of the LDA method.

LDA works when the measurements made on independent variables for each observation are continuous quantities. When dealing with categorical independent variables, the equivalent technique is discriminant correspondence analysis of Decision Tree Classifier is a simple and widely used classification technique. It applies a straightforward idea to solve the classification problem. Decision Tree Classifier poses a series of carefully crafted questions about the attributes of the test record. Each time time it receive an answer, a follow-up question is asked until a conclusion about the calss label of the record is reached.

3.3 Decision Tree Based Method

The decision tree classifiers organized a series of test questions and conditions in a tree structure. The following figure 4 shows a example decision tree for predictin whether the person cheats. In the decision tree, the root and internal nodes contain attribute test conditions to separate recordes that have different characteristics. All the terminal node is assigned a class lable Yes or No.



Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Fig. 4. Decision Tree Method for Clasification

Here figure 5 is showing the decision tree based class mapping and taking the final class based decision. Once the decision tree has been constructed, classifying a test record is straightforward. Starting from the root node, we apply the test condition to the record and follow the appropriate branch based on the outcome of the test. It then lead us either to another internal node, for which a new test condition is applied, or to a leaf node. When we reach the leaf node, the class lable associated with the leaf node is then assigned to the record, As shown in the following figure , it traces the path in the decision tree to predict the class label of the test record, and the path terminates at a leaf node labeled NO.

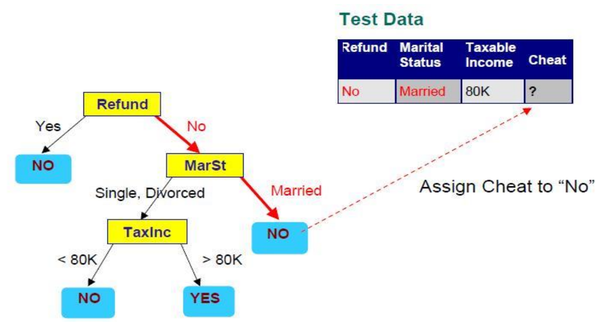


Fig. 5. Class Identification using Decision Tree

3.4 Naive Bayes Classifier

The Naive Bayes Classifier technique is based on the so-called Bayesian theorem and is particularly suited when the dimensionality of the inputs is high. Despite its simplicity, Naive Bayes can often outperform more sophisticated classification methods.

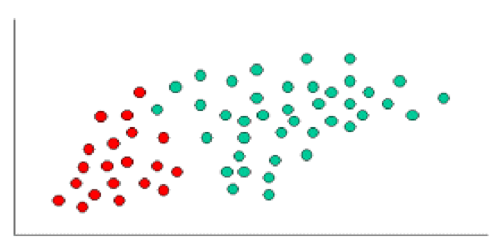


Fig. 6. Naïve Bays Clssifier

To demonstrate the concept of Naive Bayes Classification, consider the example displayed in the illustration above. As indicated, the objects can be classified as either GREEN or RED. Our task is to classify new cases as they arrive, i.e., decide to which class label they belong, based on the currently exiting objects.

Since there are twice as many GREEN objects as RED, it is reasonable to believe that a new case (which hasn't been observed yet) is twice as likely to have membership GREEN rather than RED. In the Bayesian analysis, this belief is known as the prior probability. Prior probabilities are based on previous experience, in this case the percentage of GREEN and RED objects, and often used to predict outcomes before they actually happen.

Thus, we can write:

$$\text{Prior probability for GREEN} \propto \frac{\text{Number of GREEN objects}}{\text{Total number of objects}}$$

$$\text{Prior probability for RED} \propto \frac{\text{Number of RED objects}}{\text{Total number of objects}}$$

Since there is a total of 60 objects, 40 of which are GREEN and 20 RED, our prior probabilities for class membership are:

$$\text{Prior probability for GREEN} \propto \frac{40}{60}$$

$$\text{Prior probability for RED} \propto \frac{20}{60}$$

Having formulated our prior probability, we are now ready to classify a new object (WHITE circle). Since the objects are well clustered, it is reasonable to assume that the more GREEN (or RED) objects in the vicinity of X, the more likely that the new cases belong to that particular color. To measure this likelihood, we draw a circle around X which encompasses a number (to be chosen a priori) of points irrespective of their class labels. Then we calculate the number of points in the circle belonging to each class label. From this we calculate the likelihood:

$$\text{Likelihood of } X \text{ given GREEN} \propto \frac{\text{Number of GREEN in the vicinity of } X}{\text{Total number of GREEN cases}}$$

$$\text{Likelihood of } X \text{ given RED} \propto \frac{\text{Number of RED in the vicinity of } X}{\text{Total number of RED cases}}$$

From the illustration above, it is clear that Likelihood of X given GREEN is smaller than Likelihood of X given RED, since the circle encompasses 1 GREEN object and 3 RED ones. Thus:

$$\text{Probability of } X \text{ given GREEN} \propto \frac{1}{40}$$

$$\text{Probability of } X \text{ given RED} \propto \frac{3}{20}$$

4. CONCLUSION

In this paper, an exploration to the SAR image characterization and classification is provided. The paper has identified some of the application areas of SAR image processing. The paper also provided the description of some of common classification methods. These methods are defined based on distance level, probabilistic and decision criteria specification. Decision Tree, KNN, Bayesian Network and LDA methods are defined with relative procedure and constraints in this paper.

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