A New Classification Approach for PolSAR Images

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Abstract

PolSAR images provide more information than the conventional radar images and so greatly improves the ability to terrain discrimination. This work is focused on the problem of the classification of different terrain types of PolSAR images. The proposed method uses a combination of two different classifiers. This method is named as Meta classifier and compared with other competitive classifiers. One as a spatial partitioning method, assigning each leaf of tree a distinct region label. So they are called as clustering trees. The other one is used as the second classifier for generating the class labels. But the final result is generated by voting over the ensemble results of the two classifiers. The experimental results obtained so far, indicate the potential of this approach.

Keywords

Feature evaluation, feature selection, multifeature combination, SAR image classification

1. Introduction

Environmental monitoring, earth-resource mapping, and military systems require broad-area imaging at high resolutions. Many times the imagery must be acquired in inclement weather or during night as well as day. Synthetic Aperture Radar (SAR) provides such a capability. SAR systems take advantage of the long-range propagation characteristics of radar signals and the complex information processing capability of modern digital electronics to provide high resolution imagery. SAR complements photographic and other optical imaging capabilities because of the minimum constraints on time-of-day and atmospheric conditions and because of the unique responses of terrain and targets to radar frequencies. SAR is a radar technology that is used from satellite. It produces high resolution images of earth’s surface by using special signal processing techniques. SAR has important role in gathering information about earth’s surface because it can operate under all kinds of weather condition such as cloudy, hazy or dark.

T. Zou et al., classify the terrain by using polarimetric SAR imagery has been a very active research field over recent years [1]. Although lots of features have been proposed and many classifiers have been employed, there are few works on comparing these features and their combination with different classifiers. F. Moosmann et al., introduce three new contributions to the problems of image classification and image search [2]. B. Kalpana et al., given a choice of classifiers each performing differently on different datasets the best option to assume is an ensemble of classifiers [3]. J. S. Lee et al., propose a new method for unsupervised classification of terrain types and man-made objects using polarimetric SAR data [5]. This technique is a combination of the unsupervised classification based on polarimetric target decomposition and the maximum likelihood classifier based on the complex Wishart distribution for the polarimetric covariance matrix. J. S. Lee et al., introduce three new contributions to the problems of image classification and image search [4]. Y. Yamaguchi, et al., said that a four-component scattering model is proposed to decompose polarimetric SAR images [6]. A. Freeman said that two simple scattering mechanisms are fitted to polarimetric SAR observations of forests [7]. The rest of this paper is organized as follows: In Section 2, methodology and various classifiers are formulated. Section 3 deals with the results and discussion. Finally, the concluding remarks are given in Section 4.

2. Methodology

META classifier is a combination of ERCF and KNN classifiers. Polarimetric features are divided into two categories: one is the features based on the original data and its simple transform, and the other is based on target decomposition theorems. The first category features mainly include the sinclair scattering matrix, the covariance matrix, the coherence matrix, and several polarimetric parameters. When analyzing polarimetric SAR data, there are also a number of parameters that have useful physical interpretation such as amplitude of HH-VV correlation coefficient, HH-VV phase difference, copolarized ratio in dB,
cross-polarized ratio in dB, ratio HV/VV in dB, copolarization ratio, and depolarization ratio.

2.1 Classifiers

2.1.1 Efficiently Randomized Clustering Forests (ERCF)

ERCF forests consist of randomized decision trees which predict class labels \( c \) from visual descriptor vectors of local regions \( d = \{ f_1, \ldots, f_D \} \), where \( f_i \), \( i = 1, \ldots, D \) are elementary scalar features. We train the trees using a labeled training set \( L = \{ d_n, c_n \}, (n=1, \ldots, N) \), where we assume that all descriptors sampled from a given image share the same label \( c \). During a query, each local descriptor \( d \) sampled from the query image traverses each tree from the root down to a leaf. Each tree assigns a unique leaf index to the visual descriptor and not the descriptor label \( c \) associated with the leaf during training. Thus, for each descriptor \( d \), the ERC-forest returns a set of leaf indices, one for each tree, corresponding to the associated visual descriptor. The trees are built recursively in a top down manner, as in algorithm. We start building each tree from the complete training set \( L_0 = L \), which corresponds to the complete descriptor space \( R \) [24].

Algorithm: tree growing algorithm

\begin{verbatim}
Tree (L): {Create a (sub)tree from labeled training set L}

if stopsplitting (L) = true then
  return createLeafNode (L)
else
  tries := 0
  repeat
    tries := tries + 1
    select an attribute number randomly
    select a threshold \( t \) randomly
    split \( L_t \) according to test \( T : \{ f_i < Q_t \} \) and
    Calculate score:
    \( L_s := \{ f \in L | f_i < Q_t \} \)
    \( L_r := \{ f \in L | f_i > Q_t \} \)
    score := Sc(L,T)
    until (score \( \geq S_{min} \)) or (tries \( \geq T_{max} \))
    select \( i_t, Q_t \) that achieved highest score
    return create Decision Node \((i_t, Q_t, \text{Tree}(L_s), \text{Tree}(L_r))\)
end if
\end{verbatim}

At each node \( t \), there are two children \( L_s \) and \( L_r \) created by choosing a Boolean test \( T_t \) that divides \( L_t \) into two disjoint subsets \( L_s = L_t \cap L \), with \( L_t \cap L_r = 0 \). Recursion continues with \( L_s \) and \( L_r \) until further subdivision is impossible: either all surviving training examples belong to the same class or all have identical values for all feature attributes. In the algorithm, this criteria is checked by the function stop splitting ( ). We use thresholds on elementary features as tests \( T_i = \{ f_i \leq Q_t \} \) for some feature index \( i \) and threshold \( Q_t \). The tests are selected randomly as follows: A feature index \( i \) is chosen randomly, a threshold \( Q_t \) is sampled randomly from a normal distribution and the resulting node is scored over the surviving points by using the Shannon entropy:

\[ S_c(L,T) = \frac{2\cdot I_c(T)}{H_c(L) + H_T(L)} \]  

(1)

\( H_c \) denotes the entropy of the class distribution in \( L \):

\[ H_c(L) = -\sum_{c \in C} \frac{n_c}{n} \log_2 \frac{n_c}{n} \]  

(2)

Where \( n \) is the size of the current set \( L \) and \( n_c \) is the number of descriptor vectors in \( L \) belonging to class \( c \). It is maximal when all of the \( n_c \) are equal. Similarly, the split entropy \( H_T \) is defined for the test \( T \) which splits the data into two partitions:

\[ H_T(L) = -\sum_{p=1}^{2} \frac{n_p}{n} \log_2 \frac{n_p}{n} \]  

(3)

The maximum is again reached when the two partitions have equal size. Based on the entropy of a given set, the impurity of a test can be calculated by the mutual information \( I_{c\rightarrow T} \) of the split:

\[ I_{c\rightarrow T}(L) = H_c(L) - \sum_{p=1}^{2} \frac{n_p}{n} H_c(L_p) \]  

(4)

The method of feature index selection and threshold selection is repeated until the score is higher than a fixed threshold \( S_{min} \) or until a fixed maximum number \( T_{max} \) of trials have been made. The test \( T_t \) that achieved the highest score is adopted and the recursion continues. The parameters \( (S_{min}, T_{max}) \) control the strength and randomness of the generated trees. High values produce highly discriminant trees with little diversity, while \( S_{min} = 0 \) or \( T_{max} = 1 \) produce completely random trees [24]. In this way, we build the trees as classification trees but use them as clustering trees. One can also think about the test \( T \) as a hyper plane in the descriptor space \( R \). Hence, a given test \( T_t \) divides the corresponding space \( R_i \) into two disjoint regions, \( R_i = R_t \cup R_r \), with \( R_t \cap R_r = 0 \). The split of the region, of course, then results in the split of the training set \( L_t \) [24].

2.1.2 k-Nearest neighbour (KNN)

A drawback of ERCF classifier which classifies data when all attributes of test data matches exactly with at least one instance of train data. In real life scenarios many test records will not be classified because they do not exactly match any of the training records. A more sophisticated approach, \( k \)-nearest neighbor (KNN) classification finds a group of \( k \) objects in the training set that are closest to the test object, and bases the assignment of a label on the
2.1.3. Proposed classifier

The proposed classifier is Meta classifier. Meta classifier focuses on predicting the right algorithm for a particular problem based on characteristics of the database. A classifier ensemble, consists of a set of n classifiers \( C_1, \ldots, C_n \) called base-level classifiers and a meta-level classifier CML that learns how to combine the predictions of the base-classifiers. The base-classifiers are generated by applying n different classification algorithms on a labelled dataset, the training set, \( \text{TRAINSET} = \{(x_k, y_k)\} \), where \( x_k \) and \( y_k \) are the features and the class value for the \( k \)-th instance vector respectively. The individual predictions of the base-classifiers on a different labeled dataset \( \text{TESTSET} \), are used to train the meta-classifier CML. The predictions of the base-classifiers on \( \text{TESTSET} \) are then transformed into a meta-level set of classification vectors. At runtime, CML combines the predictions \( \text{PM}(x) = \{ P_i(x), i = 1 \ldots n \} \) of the \( n \) base classifiers on each new instance \( x \), from the test data and decides upon the final class value \( y(x) \). The final predictions of the base-classifiers on \( x \) are transformed into a single vector representation, which is then classified by CML. In stacking we use multiple algorithms and combine their results. The output from the previous layer is passed as input to the next layer. The output of a decision tree and can be used as input for a neural network.

Here, we propose a two-step Meta classifier stack generalization for predicting accurate results. The first step pre-process and selects the features required for classification and the second step uses base classifiers and a meta learning algorithm to induce a meta classifier based on probability distribution of base level classifiers.

2.1.4 Automatic Feature Combination

Automatic selection and combining different feature types are always necessary when facing a large number of feature types. Since there may exist many relevant and redundant information between different feature types, we need to not only consider the classification accuracies of different feature types but also keep track of their correlations. In this section, we propose a metric-based feature combination to balance the feature dependence and classification accuracy. Given a feature type pool \( F_i (i = 1, 2, \ldots, N) \), the feature dependence of the \( i \)-th feature type is defined as

\[
\text{Dep}_i = \frac{N-1}{\sum_{j=1,j\neq i}^N \text{corrcoef}(P_i, P_j)}
\]

\[
R_i = \text{Dep}_i/A_i
\]

where \( A_i \) is the average accuracy of the \( i \)-th feature type. If the selection metric \( R_i \) is low, the corresponding feature type will be selected with low probability. While the selection metric \( R_i \) is high, it is more likely to be selected. After obtaining classification accuracy of each feature type, we propose to make feature combination by completely automatic combining method as flowchart from Fig.1. The features with higher selection metric have higher priority to be selected, and the feature is finally selected only if it can improve the classification accuracy based on the selected features with a predefined threshold.
Following the above mentioned three heuristic criterions and Table 2 we can obtain a combined feature set as \{F_1, F_2, F_4, F_7, F_9\}, which is expected to get comparable performance than combination of all the features. It can be learned that the selected feature set gets a slightly higher average accuracy. We also find that the multifeatures combination can greatly improve the performance by 4 to 8%. When selecting three feature types in the first category and two feature types in the second category using the KNN classifier, we can get the same combination result as heuristic feature combination.

The features with higher selection metric have higher priority to be selected, and the feature is finally selected only if it can improve the classification accuracy based on the selected features with a predefined threshold. In the following experiment some intermediate feature combination states are selected to illustrate that the feature combination strategy can improve the classification performance step by step. The intermediate feature combination states include the following:

Pset1: select 1 feature type in the first category and 1 feature type in the second category; the combination features include \(F_2\) and \(F_9\).

Pset2: select 2 feature type in the first category and 1 feature type in the second category; the combination features include \(F_1, F_2\) and \(F_9\).

Pset3: the final selected feature set \(\{F_1, F_2, F_4, F_7, F_9\}\).

3. Results and discussions

PolSARpro v.4.0 software is used for classification of various land features. The land features include ocean, clear water, settlements, agriculture fields, arid lands, grown and young forest, hilly terrain, mangrove forest, etc. The data acquired is processed by PolSARpro v4.0 software for classification of various land features. The software is freely available on the internet and is developed by ESA. The set of nine independent parameters of this particular parameterization allows a physical interpretation of the target. On the whole, the investigated typical polarimetric features include:

F1: amplitude of upper triangle matrix elements of S
F2: amplitude of upper triangle matrix elements of C
F3: amplitude of upper triangle matrix elements of T
F4: the polarization parameters
F5: the three parameters \(|\alpha|^2, |\beta|^2, |\gamma|^2\) of the Pauli decomposition
F6: the three parameters \(k_s, k_d, k_h\) of the Krogager decomposition
F7: the three scattering power components \(P_s, P_d, P_v\) of the Freeman-Durden decomposition;
F8: the three parameters \(H - \alpha - A\) of the Cloude pottier decomposition
F9: the nine parameters of the Huynen Decomposition.

These features are shown in Fig. 2.

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**Fig. 2.1:** Krogager \(k_d\) db
**Fig. 2.2:** Krogager \(k_h\) d
**Fig. 2.3:** Krogager \(k_s\) db
**Fig. 2.4:** Huynen RGB
**Fig. 2.5:** Huynen T11 db
**Fig. 2.6:** Huynen T22 db
**Fig. 2.7:** Huynen T33 db
**Fig. 2.8:** Freeman dbl db
**Fig. 2.9:** Freeman odd db
**Fig. 2.10:** Freeman RGB
**Fig. 2.11:** Freeman Vol db

**Fig. 2:** Different Polarimetric features extracted with the help of PolSARpro.
Table 1: Classification accuracy of single polarimetric Descriptor using KNN & ERCF

<table>
<thead>
<tr>
<th>Features</th>
<th>Classifiers</th>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class 4</th>
<th>All Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1</td>
<td>ERCF</td>
<td>68</td>
<td>39</td>
<td>63</td>
<td>81</td>
<td>68.75</td>
</tr>
<tr>
<td></td>
<td>KNN</td>
<td>84</td>
<td>30</td>
<td>2</td>
<td>43</td>
<td>39.25</td>
</tr>
<tr>
<td>F2</td>
<td>ERCF</td>
<td>88</td>
<td>34</td>
<td>69</td>
<td>72</td>
<td>69.5</td>
</tr>
<tr>
<td></td>
<td>KNN</td>
<td>99</td>
<td>20</td>
<td>4</td>
<td>0</td>
<td>30.75</td>
</tr>
<tr>
<td>F3</td>
<td>ERCF</td>
<td>69</td>
<td>41</td>
<td>67</td>
<td>76</td>
<td>63.85</td>
</tr>
<tr>
<td></td>
<td>KNN</td>
<td>87</td>
<td>39</td>
<td>11</td>
<td>36</td>
<td>43.25</td>
</tr>
<tr>
<td>F4</td>
<td>ERCF</td>
<td>69</td>
<td>45</td>
<td>64</td>
<td>78</td>
<td>64</td>
</tr>
<tr>
<td></td>
<td>KNN</td>
<td>86</td>
<td>28</td>
<td>0</td>
<td>84</td>
<td>49.5</td>
</tr>
<tr>
<td>F5</td>
<td>ERCF</td>
<td>66</td>
<td>43</td>
<td>65</td>
<td>86</td>
<td>65</td>
</tr>
<tr>
<td></td>
<td>KNN</td>
<td>88</td>
<td>8</td>
<td>2</td>
<td>78</td>
<td>44</td>
</tr>
<tr>
<td>F6</td>
<td>ERCF</td>
<td>73</td>
<td>53</td>
<td>77</td>
<td>86</td>
<td>72.25</td>
</tr>
<tr>
<td></td>
<td>KNN</td>
<td>90</td>
<td>23</td>
<td>5</td>
<td>93</td>
<td>52.75</td>
</tr>
<tr>
<td>F7</td>
<td>ERCF</td>
<td>53</td>
<td>36</td>
<td>49</td>
<td>47</td>
<td>46.25</td>
</tr>
<tr>
<td></td>
<td>KNN</td>
<td>94</td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>26</td>
</tr>
<tr>
<td>F8</td>
<td>ERCF</td>
<td>61</td>
<td>51</td>
<td>54</td>
<td>50</td>
<td>54</td>
</tr>
<tr>
<td></td>
<td>KNN</td>
<td>41</td>
<td>54</td>
<td>56</td>
<td>73</td>
<td>56</td>
</tr>
<tr>
<td>F9</td>
<td>ERCF</td>
<td>69</td>
<td>36</td>
<td>54</td>
<td>48</td>
<td>31.75</td>
</tr>
<tr>
<td></td>
<td>KNN</td>
<td>92</td>
<td>6</td>
<td>18</td>
<td>2</td>
<td>29.5</td>
</tr>
</tbody>
</table>

The SAR images are classified by using 3 different algorithms, namely ERCF, KNN and Meta algorithms. The performance of these three algorithms is compared using efficiency for given samples. The results showed that, among these three algorithms the META algorithm gives better classification results over the ERCF and KNN algorithms. The MATLAB simulation result will have very large no of values. So, the region of interest (ROI) is cropped from the MATLAB simulation result. The cropped image is mapped into for labels: red, green, blue and dark red as shown in Fig. 3.

Table 2: Set of Multifeature combinations

<table>
<thead>
<tr>
<th>S. No.</th>
<th>Threshold (T)</th>
<th>Optimal Feature</th>
<th>Features in Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4</td>
<td>Pset1</td>
<td>F2, F9</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>Pset2</td>
<td>F1, F2, F9</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>Pset3</td>
<td>F1, F2, F4, F7, F9</td>
</tr>
</tbody>
</table>

Table 3: Performance of different classifiers.

<table>
<thead>
<tr>
<th>Feature sets</th>
<th>Average classification accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ERCF (%)</td>
</tr>
<tr>
<td>Complete</td>
<td>52.5</td>
</tr>
<tr>
<td>Single</td>
<td>46-72</td>
</tr>
<tr>
<td>Multiple</td>
<td>64-70</td>
</tr>
</tbody>
</table>

This table shows the optimal multiple feature set that has been selected with multifeature combination algorithm. Threshold shows the improvement in percentage accuracy that must be achieved for adding the single polarimetric feature to optimal feature set.

Table 4: Comparison of KNN, ERCF, META efficiency

<table>
<thead>
<tr>
<th>Feature</th>
<th>Efficiency in terms of samples</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ERCF</td>
</tr>
<tr>
<td>F1</td>
<td>70</td>
</tr>
<tr>
<td>F2</td>
<td>68</td>
</tr>
<tr>
<td>F3</td>
<td>59.2</td>
</tr>
<tr>
<td>F4</td>
<td>70.8</td>
</tr>
<tr>
<td>F5</td>
<td>63.6</td>
</tr>
<tr>
<td>F6</td>
<td>62.4</td>
</tr>
<tr>
<td>F7</td>
<td>70.4</td>
</tr>
<tr>
<td>F8</td>
<td>71.2</td>
</tr>
<tr>
<td>F9</td>
<td>68.4</td>
</tr>
<tr>
<td>F10</td>
<td>70</td>
</tr>
<tr>
<td>F11</td>
<td>69.6</td>
</tr>
<tr>
<td>F12</td>
<td>63.6</td>
</tr>
</tbody>
</table>

4. Conclusions

Proposed method named as META (combination of ERCF & KNN) uses the extremely randomized trees as spatial portioning method at the base for cluster formation. Then KNN is used at cluster level for assigning the class labels. Final classification map is generated by voting over the ensemble of trees. The classification accuracy has been improved compared to the other competitive classifiers. The results
reveal that with the single feature dimension there is large variance in the classification accuracy among different classes with each classifier. Multifeature combination results in variance reduction. The META is a promising approach for POLSAR image classification and deserves the particular attention towards its use. In future, we will focus our attention towards more features such as texture; shape etc. to perform more efficient feature selection.

References


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