Game Theoretic Classification of Polarimetric SAR images

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Abstract
This paper reports on a region based classification of polarimetric synthetic aperture radar (PolSAR) images using the concept of game theory. The proposed method mainly contains the following steps. Firstly, the PolSAR image is partitioned into over-segments using an adaptation of k-means approach. Then, in order to compute the similarity between two distinct over-segments, a measure from polarimetric features and region size is defined. Finally, the regions or over-segments are merged into the meaningful clusters using a game theory based approach. In the game theory way, region merging problem is transformed into an iterative figure/ground separation state. In other words, considering the similarity measure, over-segments that belong to the figure compete with others through the game and obtain a considerable advantage in comparison with others. Accordingly, these privileged over-segments can be merged as an individual cluster. For clustering of the remaining over-segments, the procedure should be repeated. The performance of the proposed classification framework on simulated and real data sets is presented and analyzed; and the experimental results show that the framework provides a promising solution for classification of PolSAR images.

Keywords: Game theory, polarimetric synthetic aperture radar images, region based classification.

Introduction
Polarimetric synthetic aperture radar image classification is an important and continually developing issue in the automatic analysis of remote sensing data. According to the increasing available volume of polarimetric data due to the launch of polarimetric imaging sensors like RADARSAT-2, TerraSAR-X and ALOS-PALSAR, the development of automatic systems for polarimetric SAR image interpretation is urgently required and widely studied [Liu and Gierull, 2007; Lee and Pottier, 2009; Liu et al., 2013]. Maximum likelihood classifiers based on the assumption of Wishart-distributed classes have been developed [Lee et al., 1994; Lee et al., 1999]. Classification of multi-look polarimetric SAR imagery based on complex Wishart distribution with adaptive number of
clusters is proposed in [Cao et al., 2007]. Another approach [Rignot and Chellappa, 1992], which assumes complex Gaussian class distributions, also incorporates a Markov random field spatial context model that overcomes some of the effects of noise by smoothing the segmentation according to local interactions between pixel labels. In the developed techniques for the classification of polarimetric SAR images, pixel-based methods have achieved suitable results. However, due to speckle, the traditional pixel-based methods still have drawbacks [Reigber et al., 2010]. In contrast, region based approaches provided a promising scheme by improving the classification accuracy, reducing the algorithm execution time and being more convenient for updating the database [Liu et al., 2013]. However, the accuracy of region based classification greatly depends on the ways of over-segment generation and region merging [Liu et al., 2013]. For the interesting and pioneering researches of over-segment generation, the reader can refer to works of [Geman and Geman, 1984; Li, 1995; Shi and Malik, 2000; Ersahin et al., 2010; Bombrun et al., 2011; Yu et al., 2012]. In this paper, adaptation of k-means algorithm proposed by Achanta et al. [2012], as a simple, fast and accurate method is considered for partitioning of polarimetric SAR image into the efficient regions. The considered method beside the polarimetric information takes the spatial relations between pixels into account, which makes the procedure more effective and the results more understandable.

Recently, several researches have been performed for accurate region merging of PolSAR images. In Liu et al. [2013], the region merging is completed using the Wishart clustering proposed by Lee et al. [1994]. In Lang et al. [2012], statistical region merging (SRM) is presented for grouping the similar over-segments. It should be noted that comparing SRM with our employed method is discussed in detail in section 3. A binary partition trees on a dissimilarity measure in order to identify similar areas and define the merging sequence is proposed in Alonso-González et al. [2012]. A decision tree clustering have implemented in Zhang et al. [2011]. In Li et al. [2008], support vector machines are employed for the classification of different regions.

In this paper, another technique of region merging, based on the concept of game theory is considered. In this way, the region merging problem is transformed into an iterative figure/ground separation problem in a non-cooperative game theory approach. In this procedure, each over-segment belongs to the figure competes with others. Competition will allow the over-segments belong to the figure obtain a considerable advantage in comparison with others. Accordingly, these privileged regions can be merged and considered as a single cluster. Since the competition is designed by the similarity measure between the regions, it is clear that adopting an appropriate similarity function produces more valuable results. In this paper, a mixture of features is employed which combines the typical polarimetric features and the region size.

The rest of the paper is organized as follows: Section 2 introduces the PolSAR data. Section 3 discusses in details the procedure of proposed classification. The experimental results and analyses are given in Section 4. Conclusion and discussions are given in Section 5.

**Polarimetric SAR data**

Fully polarimetric SAR system measures the amplitude and phase of backscattered signals in the form of four combinations of the linear horizontal (H) and vertical (V) transmitting and receiving polarizations i.e. HH, HV, VH, and VV. Accordingly, information about
objects can be obtained from the 2×2 complex scattering matrix [S] [Lee and Pottier, 2009]. In order to best extract physical information from the scattering matrix, coherence matrices \( T = \langle K K^\dagger \rangle \) and covariance matrices \( C = \langle \Omega \Omega^\dagger \rangle \) can be constructed using two target vectors \( K = 1/\sqrt{2} [s_{HH} + s_{VV}, s_{HV} - s_{VH}, 2s_{HVV}] \) and \( \Omega = \begin{bmatrix} s_{HH} & s_{HV} & s_{VH} \end{bmatrix} \) through the vectorization procedure, where \( * \) and \( \dagger \) represent the complex conjugate and the matrix transpose operations, respectively, and \( \langle .. \rangle \) denotes the spatial average over a window size [Lee and Pottier, 2009].

Each extracted parameter of a POLSAR image can be expressed as a feature. Polarimetric SAR images provide several valuable features, which are very useful for physical interpretation. Some features can be computed from the original data, which include the scattering matrix, the covariance matrix, the coherence matrix and several polarimetric parameters; and some other can be obtained from target decomposition theorems. Table 1 lists the 27 considered features.

**Table 1 - Polarimetric parameters used in this study.**

| Feature                      | Description                                      | Symbol                                                                 | Number |
|------------------------------|--------------------------------------------------|------------------------------------------------------------------------|--------|
| **Original features**        | Amplitude of upper triangle matrix elements of S | \(|S_{HH}|, |S_{HV}| and |S_{VV}|\)                  | 3      |
|                              | Amplitude of upper triangle coherence matrix elements | |                                | 6      |
|                              | Amplitude of upper triangle covariance matrix elements | |                                | 6      |
|                              | span of the scattering matrix                     | \(|S_{HH}|^2 + |S_{HV}|^2 + |S_{VV}|^2\)                        | 1      |
|                              | Ratio VV/HH [Zou et al. 2010]                     | \(10 \log \left( \frac{|s_{VV}|^2}{|s_{HH}|^2} \right)\)          | 1      |
|                              | Ratio HV/HH [Zou et al. 2010]                     | \(10 \log \left( \frac{|s_{HV}|^2}{|s_{HH}|^2} \right)\)          | 1      |
|                              | Ratio HV/VV [Zou et al. 2010]                     | \(10 \log \left( \frac{|s_{HV}|^2}{|s_{VV}|^2} \right)\)          | 1      |
|                              | Depolarization ratio [Zou et al. 2010]           | \(\frac{\langle s_{HH}^* s_{HV} \rangle}{\langle s_{HH}^* s_{HH} \rangle + \langle s_{VV}^* s_{VV} \rangle}\) | 1      |
|                              | Correlation Coefficient [Zou et al. 2010]        | \(\frac{\langle s_{HH}^* s_{VV} \rangle}{\sqrt{|s_{HH}|^2 |s_{VV}|^2}}\) | 1      |
| **Decomposition features**   | Pauli decomposition [Lee and Pottier 2009]        | \(\alpha, \beta\) and \(\gamma\)                                     | 3      |
|                              | Cloude-Pottier decomposition [Cloude and Pottier 1997] | entropy \((H)\), alpha \((\alpha)\), and anisotropy \((A)\)     | 3      |

**Game theoretic classification**

In this paper, application of game theory is studied for the polarimetric SAR image classification. Figure 1 presents the flowchart of proposed method. Polarimetric features...
include valuable information to improve the discrimination power. As clearly depicted in Figure 1, firstly, the listed features in Table 1 is computed. Then, feature selection is performed with the aim of taking the advantages of all features, and then the first three elements of reduced features are considered in the next stages. It should be noted that five different feature selection methods namely principal component analysis (PCA) and kernel based PCA (KPCA) [Tenenbaum et al., 2000], independent component analysis (ICA) [Hyvärinen and Oja, 2000], factor analysis (FA) [Harman, 1976] and manifold charting (MC) [Brand, 2003], are implemented, evaluated and compared to define their performance within the classification framework. It should be noted that the dimension reduction software tool are taken from Van Der. Maaten’s matlab toolbox [Maaten, 2013]. In the following the procedure of classification is discussed in two subsections. First part presents a brief description of over-segment generation and the second part gives a solution for region-merging problem using the concept of game theory.

**Figure 1 - The flowchart of game theoretic classification.**

**Over-segment generation**
Over-segments are generated using the first three components of the reduced features in order to improve the accuracy and efficiency of PolSAR image classification. Achanta et al. [2012], presented a simple, fast and accurate method using an adaptation of k-means algorithm for over-segment generation. Taking the spatial relations between pixels into
account and limiting the search space are the main characteristics of this adaptation method in comparison with the standard k-means algorithm [Achanta et al., 2012]. In other words, distance measure is constructed using the polarimetric information as well as the spatial relationship. Limited search space led to assign pixel to the region from its neighborhood. Similar to the standard k-means, the adapted method assigns pixel to clusters based on the minimum distance rule. The distance \( d \) between pixel \( p \) and over-segment \( q \) in adaptation method can be defined as follows.

\[
d = \sqrt{d_1^2 + d_2^2}
\]

\[
d_1 = \sqrt{\sum_{i=1}^{3} (r_i^p - r_i^q)^2}
\]

\[
d_2 = (x^p - x^q)^2 + (y^p - y^q)^2
\]  \[1\]

Where \( r_i, i=1,2,3 \) are the first three components of reduced features, \( x, y \) represent the position of pixel and region’s center, respectively. More details and information about this method can be found in [Achanta et al., 2012]. Moreover, the procedure of adapted k-means method is presented as following algorithm.

Algorithm of adapted k-means for over-segment generation [Achanta et al., 2012]

1. Divide image into the regular grid with \( M \times N \) tiles, where \( M=\)image width/region width and \( N=\)image height/ region height.
2. Construct the initial regions from the average of pixels in regular grids.
3. Run k-means algorithm to get the new regions, while the search space is limited to a neighborhood.

Region merging

After construction of over-segment using adapted k-means, game theory is employed for regions merging. According to [Taylor and Jonker, 1978], game theory is the study of optimization in situations of strategic interaction between one or more individuals. In the game theory framework, there is a formal model (called game) that typically comprises the set of individuals who interact (called players) and the different choices available to each of the individuals (called actions or pure strategies), and a payoff function that assigns a value to each individual for each possible combination of choices made by every individual. It should be noted that the game theoretic procedure have already been applied to the different fields of computer vision, especially matching and grouping [Torsello et al., 2006; Albarelli et al., 2009; Albarelli et al., 2012].

In region merging problem in the game theoretic way, there are two players that select over-segments simultaneously. It is in each player’s interest to pick the over-segments that are compatible with those the other player is likely to choose. Accordingly, the selected over-segments by the players have the high internal coherency among themselves to belong to a specific cluster. Therefore, these over-segment can be merged as an individual cluster. Subsequently, in order to clustering of the remaining over-segments into different clusters, the selection by the players will continue iteratively until clustering of all regions.

Game theory is an evolutionary process. In the considered procedure, the game is initialized with a constant probability for all over-segments. In other words, the probability of choosing
the over-segments by the players is initially constant i.e. $x = [1 \ldots 1] / n$, where $x$ is the probability vector for $n$ over-segments. Through the game, each player is preprogrammed to select over-segments with a certain probability. According to the [Taylor and Jonker, 1978], the evolutionary selection allows the players to select the over-segments that have the high probability. Referring to [Taylor and Jonker, 1978], the evolutionary selection process can be given as:

$$x_{k+1} = x_k \times \frac{D \times x_k}{x_k^T \times D \times x_k} \quad [2]$$

where $k$ is denote for $k^{th}$ iteration in the evolutionary process, and $D$ is similarity measure between the over-segments or the payoff function in the language of game theory, which can be defined as:

$$D_{ab} = \exp(-\frac{1}{2} \left( \sum_{i=1}^{3} \left( \frac{r_i^a - r_i^b}{\sigma_{ri}} \right)^2 + \frac{(drw_{ab})^2}{\sigma_w^2} \right)) \quad [3]$$

Where $r_i, i=1,2,3$ are the first three components of reduced features, $a$ and $b$ represent two distinct over-segments, $drw_{ab}$ is the symmetric revised Wishart distance and given as Equation [4] [Liu et al. 2013]. $\sigma_{ri}$ and $\sigma_w$ are the kernel bandwidths and can be estimated via standard deviations of reduced components and Wishart distance, respectively.

$$drw_{ab} = tr(Z_a^{-1}Z_b + Z_b^{-1}Z_a)(n_a + n_b) \quad [4]$$

In Equation [4], $tr(A)$ denotes the trace of the $A$ matrix, and $A^{-1}$ its inverse, and $Z_a, Z_b$ are the average covariance matrices of over-segments $a$ and $b$, respectively, which include $n_a$ and $n_b$ pixels. Equation [2] should be iteratively computed until the population reaches to equilibrium - in the language of the game theory - or a termination criterion is met. This equation causes that the coherent over-segments obtain a high probability through the game. Accordingly, the over-segments with high probability value are considered and merged as a single cluster. For clustering the remaining over-segments, the same procedure should be repeated until clustering all of them. It should be noted that when there is no more change in the values of $x$, the population reaches to equilibrium. In the following, the algorithm of region merging using the game theory is presented.

Algorithm of region merging using game theory approach.

1. The probability of over-segments is initially set to a constant value, $x = [1 \ldots 1] / n$;
2. Equation [2] is iteratively computed until the termination criterion is met;
3. Over-segment with high probability should be merged as a single cluster;
4. Steps 1, 2 and 3 repeat for clustering of the remaining over-segments.
Experimental results
In this section, the performance of the considered framework is presented and analyzed on synthetic and real experimental data sets. The first data set is a synthetic polarimetric image. The second data set is from a subset of an L-band, multi-look PolSAR image, acquired by the AIRSAR airborne platform in San Francisco, which is publicly available by ESA (NASA/JPL). The third data set is a subset of the fully polarimetric SAR image in Flevoland area acquired by RadarSat-2 at fine quad-pol mode provided by Canadian space agency (CSA).

Synthetic data set
In this subsection, simulated data have been generated using the Monte-Carlo-based design [Lee and Pottier, 2009]. In this model, the covariance matrix C can be given in the form of:

\[
C = \sigma \begin{pmatrix} 1 & 0 & \rho \sqrt{\gamma} \\ 0 & \varepsilon & 0 \\ \rho^* \sqrt{\gamma} & 0 & \gamma \end{pmatrix}
\] [5]

Three sets of images have been simulated according to above equation with \(\gamma=1\), \(\varepsilon=0.1\) and variations for \(\sigma\) and \(\rho\) in different six regions as portrayed in Figure 2. These simulated images are constructed as follows.
(1): Variation in intensity i.e. \(\rho=0.25\), \(\sigma=\{64,49,1,9,25,16\}\).
(2): Variations in correlation i.e. \(\sigma=1\), \(\rho=\{0.75e^{i\pi}, -0.5, 0.5e^{i\pi}, 0, 0.25, 0.25\}\).
(3): Variations both in correlation and intensity i.e. \(\sigma=\{64,49,1,9,25,16\}\) and \(\rho=\{0.75e^{i\pi}, -0.5, 0.5e^{i\pi}, 0, 0.25, 0.25\}\).

Considering these covariance matrices allow to construct the associated simulate polarimetric SAR image as discussed in detail in [Liu et al., 2013].

In order to classify the simulated images using the proposed method, firstly the polarimetric information, which lists in Table 1 are computed and then just manifold charting (MC) as a feature selection method is considered for taking the advantages of the extracted
information. First three components of MC are used for over-segment generation through the adapted k-means algorithm. The procedure of over-segments clustering is followed by computing the similarity matrix using Equation [3]. Selection process of over-segments is initialized by setting the same probability value for all over-segments. In Figure 3a, the blue line shows that in initial stage all over-segment have the same probability. In order to perform a competition in the language of game theory, new values of probability should be iteratively computed using Equation [2]. This iterative computation allows the coherent over-segments obtain high probability’s value. As clearly portrayed in Figure 3a, (red line) the probability is considerably increased for some coherent over-segments and decreased for others. Accordingly, the over-segments associated with the high probability should be merged and clustered as a single cluster. It should be noted that the iteration process (iterative computation of Eq. [3]) is continued until no more over-segments obtain high probability. In this case the over-segments with 10% of maximum probability are merged. Figure 3b shows that the population reaches to equilibrium in 54th iteration. In other worlds, after 54th iteration the number of over-segments that obtain 10% of maximum probability, does not change. Therefore, the associated over-segments should be merged. For remaining over-segments the same procedure should be repeated.

Game theoretic procedure segments the image into different clusters and the labeling of these clusters is determined by user intervention. It should be noted that, in order to evaluate the performance of the proposed method in the presence of speckle effect, the simulated images are classified without de-speckling. The performance of the final classification results is evaluated with kappa coefficient (K), overall accuracy (OA) [Congalton, 1991] and harmonic mean of the user’s and producer’s accuracies (UA and PA)[Lewis and Gale, 1994]. User’s and producer’s accuracies give a more detailed overview of the results. Ideally, both UA and PA should be high. Harmonic mean of the UA and PA is a way to construct a single quality measure by their combination as the following equation.

\[
HM_\beta = (1 + \beta^2) \cdot \frac{UA \cdot PA}{\beta^2 \cdot UA + PA} \quad [6]
\]
where $\beta$ can control putting more importance on UA or PA. We consider UA and PA to be equally important $\beta = 1$. According to Table 2 and from the global analysis based on $K$ and OA, it was concluded that classification based on the simulated data from variation in both intensity and correlation gives better result than the other two situations. HM allows to investigate this in more detail. The differences between the results depend on the way of image simulation. When the image is simulated with variations in intensity, the classifier gives better results for classes #5 and #6. For the simulated image with variations in the correlation, the best results are related to classes #1 and #2. However, for the simulated image with variations both in correlation and in intensity, the classifier gives the appropriate results for all classes. The fact that the relative behavior of the classifier with different classes seems to vary a lot in the way of data simulation, which is an indication of the importance of all element of covariance matrix in the classification procedure.

### Table 2 - Game theoretic classification accuracy for simulated data sets.

| Simulated data sets                               | Harmonic mean of UA and PA | Classification accuracy |
|---------------------------------------------------|-----------------------------|-------------------------|
|                                                   | Class 1 | Class 2 | Class 3 | Class 4 | Class 5 | Class 6 | K %  | OA%  |
| Variation both in correlation and in intensity    | 82.49   | 93.38   | 97.003  | 90.44   | 95.53   | 88.74   | 88.73 | 90.61 |
| Variation in correlation                          | 74.60   | 85.64   | 59.24   | 43.74   | 52.38   | 59.70   | 66.76 | 90.61 |
| Variation in intensity                            | 74.93   | 77.48   | 84.38   | 67.74   | 95.51   | 88.16   | 77.78 | 81.48 |

The important item in region based classification is the number of the over-segment. The low number cause under segmentation and high value of it will result in the large volume of memory and massive computations. Moreover, small over-segments are more easily affected by the speckle. Figure 4 shows the variation in classification accuracy with different number of over-segments.

![Figure 4 - Game theoretic classification accuracy (%) as a function of over-segment’s number using simulated data with variation both in intensity and correlation.](image-url)
Experiment using AIRSAR image

The San Francisco image is used to demonstrate the efficiency of the proposed technique and analyze its behavior in the classification procedure for two scenarios: 1) study to determine an optimal feature selection method on PolSAR data and 2) algorithm effectiveness for region merging in comparison with Wishart region based clustering proposed by Lee et al. [1994] and hierarchical classification based on the statistical region merging [Bombrun and Beaulieu, 2008; Bombrun et al., 2011]. In this way, the over-segments are generated using the adapted k-means and region merging are performed using these three algorithms. The ground truth of the San Francisco image gleaned from [Aghababaee et al., 2013], which contains 4040 urban pixels, 4897 ocean pixels and 3514 vegetation pixels. In the preprocessing operation, this PolSAR image is processed with the IDAN refined filter [Vasile et al., 2006]. As mentioned before, different polarimetric features are extracted aimed at improving over-segment generation. We investigated some feature selection methods e.g. PCA, KPCA, ICA, FA, and MC and compared them with each other based on the performance of the final classification results achieved by implemented approaches.

Among these feature selection methods, PCA is the fastest algorithm while KPCA is the slowest to run. The runtime for MC was more than FA and FA is more time-consuming than ICA. Table 3 presents the classification results numerically and shows the average K and OA as well as the standard deviation over the classifiers, in the two bottom rows of the table, and over the different feature selection methods in columns 7-10. From these results, it is interesting to notice that the Wishart clustering [Lee et al., 1994] gives the best result for the KPCA, while the hierarchical classification [Bombrun and Beaulieu, 2008] gives better result for manifold charting. In addition, the game theoretic classifiers gives the best result with this feature reduction method. Figure 5 shows the obtained results.

Table 2 shows that the game theory region merging produces 84.4% mean kappa accuracy which is 7.95% and 16.98% beyond the hierarchical and Wishart region merging methods, respectively. Moreover, the variation of Wishart and game theory is less than hierarchical method, this indicates that these methods have less sensitivity than the hierarchical method to the selected features. The variation in global kappa and OA over the three classifiers are between 17% and 12%, respectively. From the five feature selection methods, ICA gives the worst result for all classifiers and MC with 81.23% of mean kappa obtains the overall best result. The variation of results over the classifier is smallest with factor analysis ($\sigma_{kappa}=6.11$) and largest with the MC ($\sigma_{kappa}=14.12$). The variation over the feature selection methods is larger than the variation over the different classifiers. This underlines the importance of the choosing feature selection method in PolSAR classification.
In general, the game theoretic procedure performs efficiently for all feature selection methods. Looking at Table 3, one may note that the hierarchical classification is better than the game theoretic, when the factor analysis is considered. Whereas, in totality, the game theory outperforms the other employed methods.

### Table 3 - Comparison of classification accuracy using San Francisco image.

|                  | Game theoretic classification | Hierarchical classification | Wishart clustering |
|------------------|-----------------------------|----------------------------|--------------------|
|                  | K % | OA%  | K%  | OA% | K%  | OA % | K  | σ(k) | OA | σ(OA) |
| Factor analysis  | 79.08 | 86.10 | 83.89 | 89.24 | 71.76 | 81.17 | 78.24 | 6.11 | 85.50 | 4.07 |
| ICA              | 69.70 | 81.06 | 60.35 | 71.76 | 52.73 | 67.03 | 60.93 | 8.50 | 73.28 | 7.14 |
| Manifold charting| **92.91** | **95.28** | **85.24** | **90.18** | 65.54 | 78.84 | 81.23 | 14.12 | 88.10 | 8.41 |
| PCA              | 87.53 | 91.70 | 82.41 | 88.30 | 72.77 | 83.21 | 80.90 | 7.49 | 87.74 | 4.27 |
| KPCA             | 92.78 | 95.18 | 70.36 | 80.35 | **74.32** | **82.93** | 79.15 | 11.97 | 86.15 | 7.92 |
| Mean value       | 84.40 | 89.86 | 76.45 | 83.97 | 67.42 | 77.94 |        |      |      |      |
| Standard deviation| 9.96 | 6.17 | 10.77 | 7.86 | 8.86 | 6.87 |        |      |      |      |

### Experiment using RADARSAT-2 image

In this subsection, we used the third data set, including four classes of land covers to analyze the performance of game theoretic classification using high-resolution PolSAR images. Figure 6a is Flevoland’s image with Pauli color composed. The ground truth map that is published in the literature [Tu et al., 2012] is shown in Figure 6b. Four classes of land covers are identified, consisting of water, woodland, cropland, and buildings.
In the preprocessing operation, the PolSAR image is processed with the 5×5 IDAN filter [Vasile et al., 2006]. In order to classify the Radarsar-2 image in Flevoland area, PCA has been adapted to feature selection and over-segments are generated using the adapted k-means algorithm and illustrated on the Pauli image in Figure 6c with 10439 over-segments. The employed game theory segments the Flevoland’s image into 12 clusters. These clusters are displayed in Figure 6d. The respective final classification map that obtained by user intervention from the clustered image is shown in Figure 6e. For comparison, similar to the San Francisco image, the hierarchical and Wishart region merging methods are implemented. In order to demonstrate the effectiveness of the region based classifications in comparison with traditional pixel-based, Wishart pixel-based classification [Cloude and Pottier, 1997] has been employed for this work. Table 4 lists the classification accuracy that obtained by the aforementioned classifiers. From the experimental results in Table 4, the game theoretic classifier outperforms the other used methods. The total accuracy of the proposed method is beyond 84%, which is about 6.98%, 7.34% and 10.21% higher than the hierarchical region based and Wishart region based and Wishart pixel-based classifier, respectively. Performance of the region based classifiers in comparison with pixel-based is related to the consideration of the spatial relations between pixels. It should be noted that for the pixel-based method, in case the 5×5 filter is not enough, we increase the size of the filter to 9×9.

The confusion matrix of the game theoretic classification map is given in Table 5. From this table, parts of each class are mistakenly classified as the other land covers. Table 5 shows that water is properly distinct from woodland and building. However, some confusion with cropland can be seen. Woodland is more properly classified in comparison with the other classes. Nevertheless, the utmost confusion is between this class and building. Achieving to accuracy beyond 80% for each class demonstrates the effectiveness of the game theoretic classifier.

| Classification methods | Region based classifiers | Pixel base classifier |
|------------------------|-------------------------|----------------------|
|                        | Game theoretic region merging | Hierarchical region merging | Wishart region merging | Wishart pixel-based |
| K %                    | 79.98                   | 70.60                | 70.24                  | 66.49                 |
| OA%                    | 84.97                   | 77.99                | 77.63                  | 74.76                 |

| Ground truth | Water | Woodland | Cropland | Building |
|--------------|-------|----------|----------|----------|
| Classification |       |          |          |          |
| Water        | 83.42 | 0        | 5.66     | 0        |
| Woodland     | 2.72  | 89.71    | 7.09     | 18.25    |
| Cropland     | 13.81 | 8.75     | 87.14    | 1.54     |
| Building     | 0.05  | 1.53     | 0.01     | 80.22    |

As mentioned earlier, the termination criterion is the number of over-segments that obtain the probability more than 10% of the maximum probability. Here, we analyzed the classification performance with different percent value of the maximum probability using
the third data set. Figure 7 shows that when the percent value increases from 10% to 90%, the classification accuracy has changed just 6.66%. The high percent value makes fewer segments and consequently produces more confusion between the classes and the low value produces more clusters. In this data set, the optimum percent value is 20%, which is taken into account in Figure 6.

![Figure 7 - Game theoretic classification accuracy (%) as a function of percent value in termination criterion using RADARSAT-2 image.](image)

**Conclusion**

In this paper, a region based classification framework for polarimetric SAR images is considered. First, the over-segments are generated using an adaptation of k-means algorithm. Next, the over-segments are merged using the game theory procedure. The performance of the proposed framework analyzed in simulated and real data sets. Results show that the method provides an effective and robust solution for PolSAR image classification and its effectiveness in comparison with the other implemented methods is demonstrated. Moreover, we analyzed different feature selection methods in the classification procedure. Among them, PCA was the fastest algorithm while KPCA was the slowest algorithm to run. Employing different classifier, the Manifold charting method was more accurate in comparison with the others whereas ICA was the worst. However, PCA and KPCA had close results to the manifold charting. In the game theoretic procedure, the similarity matrix was computed using the typical polarimetric features and the region size. In addition, several features can be selected and fused into the framework easily.

For the future, the classification framework can be improved by: 1) using other information and dissimilarity measures may be more suitable or complementary, such as more complicated statistical models [Vasile et al., 2010], more components of reduced features, scattering mechanisms, texture and features like fractal information in the image [Aghababae et al., 2013]; 2) Considering the methods that employ the edge information as well as the covariance matrix information are very interesting for over-segment generation. Moreover, In order to create a fully unsupervised classification framework, the clusters that obtain from the game theory can be merged without user intervention. For this, the class labels can be determined by the final classification operation. Moreover, how to generate
the adaptive number of segments using the game theory is a question that deserves further research. Termination criterion is an important factor as depicted in Figure 7. Such aspects can be studied as a future development of this work. In addition, the framework needs to be applied to an enormous PolSAR image and compared with the new efficient methods.

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