Contextual PolSAR image classification using fractal dimension and support vector machines

Hossein Aghababaee1*, Jalal Amini1 and Yu-Chang Tzeng2

1Department of Surveying and Geomatic Engineering, University of Tehran, 1115-4563 Tehran, Iran
2Department of Electronic Engineering, National United University, 36003 Miaoli, Taiwan
*Corresponding author, e-mail address: aghababaee@ut.ac.ir

Abstract
In this paper, a new classification scheme of polarimetric synthetic aperture radar (PolSAR) images using fractal dimension as contextual information is proposed. Support vector machines (SVM) due to their ability to handle the nonlinear classifier problem are applied to a new fractal feature vector, which is constructed from Pauli decomposed vector and fractal dimensions. Fractal dimension is computed based on the concepts of fractional Brownian motion (fBm) and wavelet multi-resolution analysis using a self-adaptive window approach and fuzzy logic. The experimental results on AIRSAR images prove effectiveness of the proposed vector in comparison to the Pauli decomposed vector.

Keywords: Classification, PolSAR image, support vector machines, fractal dimension, wavelet multi-resolution.

Introduction
Remote sensing is a valuable tool in many areas of science which can help study earth processes and solves environmental and socioeconomic problems. Remote sensing gives information (in the form of satellite images) about the land use/cover. This information can be obtained using image classification. Classification is a way to assign the label of pixels to land cover and analyze the obtained information [Goumehei and Tolpekin, 2011]. Polarimetric SAR image classification plays an active role in many domains as a significant part of remote sensing image processing. PolSAR data have more independent features which can represent different physical significances than optical images. Also, many studies have reported various methods with greater classification accuracy using polarimetric radar data instead of conventional single polarization SAR data [Van Zyl, 1989; Cloude and Pottier, 1997; Aghababaee et al., 2012]. Nevertheless, how to find an effective classifier is very important for PolSAR image classification.

In various PolSAR classification experiments, many features such as intensities, coherency matrix, correlation and phase differences have been used. The first algorithms developed for
classification of polarimetric SAR images had ignored the spatial information (texture) and used the Whishart distribution as the basis of the classification scheme [Kourgli et al; 2011]. However, some research revealed the contribution of texture in polarimetric classification improvement. Recently, some authors proposed to employ texture features calculated from polarimetric data after decomposition. Beaulieu and Touzi [2004] introduced a segmentation algorithm that takes into account texture information where the K-Wishart distribution is used to model textured areas. Rodionova [2007] demonstrated that textural features defined in every scattering categories of Freeman and Durden decomposition make better object discrimination of PolSAR images. Zhang et al. [2010] combined the scattering powers of MCSM (Multiple Component Scattering Model) as a potential decomposition method and selected texture features from Gray level co-occurrence matrices using support vector machines (SVM). Zhou et al. [2010] combined the texture classification and the maximum likelihood classification based on the complex Wishart distribution for the polarimetric covariance matrix. In this method, the texture features were first extracted from the span image based on co-occurrence matrices; and then the classifier combine the texture features with the distance measure based on polarimetric information to obtain the results. Kourgli et al. [2011] proposed two segmentation approaches incorporating contextual information. The first approach was contextual fuzzy clustering based on the bias correction defined by a texture feature and the second one was a Markovian segmentation based on non-parametric textural modeling. Liu et al. [2011] proposed a method based on the log-cumulants of texture parameter of the fully polarimetric SAR data. The method uses a combination of the texture parameter and the SVM classifier based on the spherically invariant random vectors model. The texture is extremely important for radar imagery interpretation, especially in terrain mapping. In fact, radar image depends heavily on the scattering of ground objects and its textures strongly vary with different objects. Many models have been employed in texture analysis. In this study, a fractal model is adapted to extract the fractal dimension as a texture from the polarimetric images after the decomposition. In other words, a new fractal feature vector is constructed from the Pauli decomposed vector and fractal dimensions. Finally, the proposed vector is classified using the well-known SVM classifier. Implementation of SVM in the field of remote sensing is spreading gradually and gives improved results respect to traditional classifiers like maximum likelihood [Huang et al., 2002; Melgani and Bruzzone, 2004; Pal and Mathur, 2005]. In the construction of the proposed vector, fractal dimension is computed contextually from the Pauli decomposed vector. It is worth mentioning that the aim of contextual classification is to generate a smooth image classification pattern. In other words, the concept of contextual classification is that each pixel is treated in relation to its neighbor’s [Tso and Mathur, 2009]. Also, the texture is a context dependent property and texture based classification is the contextual classification [Wu and Linders, 1999]. At this paper, fractal dimension as a texture is computed in neighborhood operation; accordingly, it can be considered as contextual information. It is noteworthy that the self-adaptive window approach and fuzzy logic are used to compute the fractal dimension based on the concepts of fractional Brownian motion (fBm) and wavelet multi-resolution analysis.

**Polarimetric SAR data processing**

Polarimetric radars often measure the complex scattering matrix (S), produced by a target under study with the objective to infer its physical properties. Assuming linear horizontal
and vertical polarizations for transmitting and receiving, \( S \) can be expressed as:

\[
S = \begin{bmatrix}
S_{hh} & S_{hv} \\
S_{vh} & S_{vv}
\end{bmatrix}
\]  
[1]

Polarimetric features of PolSAR image can generally be divided into two categories: one is the features extracted directly from the polarimetric SAR data and its different transforms; the other is the features based on polarimetric target decomposition. In order to separating and identifying contributions from different types of scatterers in PolSAR data, target decomposition techniques were proposed, which are separating target scattering matrix into independent components related to the respective scattering mechanism. Several decomposition techniques have been proposed. These techniques are based on two principal approaches known as coherent and non-coherent methods. These techniques split the scattering matrix into the sum of elementary scattering matrices, each one defining a deterministic scattering mechanism [Touzi, 2007]. Pauli decomposition is one way to analyze the coherent targets and expresses as:

\[
\vec{p}_{Pauli} = \frac{1}{\sqrt{2}} \begin{bmatrix}
S_{hh} + S_{VV} \\
S_{hh} - S_{VV} \\
2S_{HV}
\end{bmatrix}
\]  
[2]

The first element of the vector expresses the odd bounce scatterer type such as the sphere, the plane surface or reflectors of trihedral. The second one is related to a dihedral scatterers or double isotropic bounce and the third element is related to horizontal and a cross polarizing associated with the diffuse scattering or volume scattering. Hence, by means of the Pauli decomposition, all polarimetric information in \( S \) can be represented in a single RGB image by combining the intensities, which determine the power scattered by different types of scatterers. In this paper, the results of applying SVM to the Pauli vector are compared with the results of the proposed feature vector.

**Fractal feature vector**

It is known that many natural surfaces exhibit fractal behavior within a certain range of scales. Such a behavior is summarized by the concept of fractal dimension, which can be related to the intuitive concept of surface roughness. The most suitable mathematical model for the random fractal found in nature, is the fractional Brownian motion, introduced by Mandelbrot and Van Ness [1968]. Specifically, fBm surface function \( V_H(x,y) \) is described by a random field having zero-mean Gaussian increments satisfying the follow relation [Betti et al., 1997]:

\[
E[V_H(x,y) - V_H(x+\Delta x,y+\Delta y)] = \| (\Delta x, \Delta y) \|^H
\]  
[3]

where \( E[.] \) is the expected value, \( \| . \| \) is the usual Euclidean norm, and \( 0<H<1 \) is the Hurst index, or persistence parameter, controlling the roughness of the surface. The fractal dimension \( D \) and the persistence parameter are related using [4] [Betti et al., 1997].
\[ D = E + 1 - H \] \[4\]

where \( E \) is the Euclidean dimension. The Euclidean dimension for images is 2 \((E=2)\) [Betti et al., 1997], so \([4]\) can be written by \(D=3-H\). Many researchers had already proven that the polarimetric SAR signal is chaotic and follows fBm [Goodman, 1976; Mcdonald et al, 2002]. According to Tzeng et al. [2007], polarimetric SAR images can be modeled in nonlinear dynamic system and characterized by its fractal dimension.

According to Figure 1, the proposed feature vector is constructed from the Pauli vector and its fractal dimensions as following equation:

\[
\vec{k}_{\text{fractal}} = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{hh+vv} & S_{hh-vv} & S_{2hv} & D(S_{hh+vv}) & D(S_{hh-vv}) & D(S_{2hv}) \end{bmatrix}^T \[5\]

where \(D(S_{hh+vv})\), \(D(S_{hh-vv})\) and \(D(S_{2hv})\) are fractal dimension of the Pauli vector elements. Using the Pauli decomposition, all polarimetric information can represent in a single RGB image. Subsequently the fractal dimension can be estimated on a specific window size over the entire of the RGB images. The value of the central pixel of the window at each position of the image is replaced by the estimated local fractal dimension. The local fractal map provides a textured image of the RGB image that is dependent on the size of local window.

![Figure 1 - Diagram of the proposed contextual classification method.](image)

A method of computing \(D\) that has been used in the present work derives from the peculiar form of the power spectrum of fBm. Since fBm is not a stationary process, fractional Brownian motion does not have a power spectrum defined in the classical sense. Nevertheless, fBm being an isotropic random field can be characterized by a random phase Fourier description.
obeying a generalized power density of the form [Parra et al., 2003]:

\[ S(w_1, w_2) = |FFT(window)|^2 \]  

\[ 6 \]

where \( S \) denotes the power spectrum, \( w_1 \) and \( w_2 \) represent two axes in the frequency domain, and FFT refers to the fast Fourier transformation of a selected window. By filtering the frequency domain signal with a wavelet filter, the resulting spectrum at a specific resolution \( j \) is:

\[ S_{2j}(w_1, w_2) = S(w_1, w_2) |\Psi_{2j}(w_1, w_2)|^2 \]  

\[ 7 \]

Where \( \Psi_{2j}(w_1, w_2) = \psi_j(w_1)\psi_j(w_2) \), and \( \psi_j(w_1) \) and \( \psi_j(w_2) \) denotes the one-dimensional wavelet functions associated with the scaling functions \( \varphi_j(w_1) \) and \( \varphi_j(w_2) \), respectively. The energy of the detailed signal at a specific resolution \( j \) can be calculated by its integration in the support of \( \Psi_{2j}(w_1, w_2) \) from a chosen wavelet filter.

\[ \sigma_{2j}^2 = \frac{2^{-2j}}{4\pi^2} \sum_{-\pi}^{\pi} \sum_{-\pi}^{\pi} S_{2j}(w_1, w_2)d\omega_1d\omega_2 \]  

\[ 8 \]

Summation of [8] at two successive resolutions allows us to obtain the following relationship [Parra et al., 2003]:

\[ D = 3 - H = 3 - 0.5 \log_2(\sigma_{2j}^2 / \sigma_{2j+1}^2) \]  

\[ 9 \]

Fractal dimension of each element depends on its neighbors. To define the neighborhood in remote sensing image analysis there is a system, which specifies some surrounding pixels as neighbors. In this paper, a self-adaptive window method based on the fuzzy logic is used. Computing fractal dimension with different window sizes will result in different dimension values. The small window is suitable for expressing the strong edges and also it is more appropriate to use a larger window for smooth surfaces such as sea area.

Fuzzy set theory is adapted for choosing the optimum size of the window from 11×11, 9×9, 7×7 and 5×5 window size by considering the difference of fractal dimension values between two successive window sizes when the size is subsequently changed from 11×11 to 5×5. If the change of the difference is high, there is a tendency to exist more than one kind of textures or image elements within the window, thus the small size of the window should be adopted. Otherwise, the current size of the window is appropriate for the estimation of that position [Novianto et al, 1999]. The criteria for the selection of window size are based on the resolution, classification specificity and the nature of the classes. However, windows with the size of 5×5 to 11×11 are commonly used for texture extraction from moderate resolution images [Pant et al., 2010]. Figure 2 shows the used membership function for the input and output parameters. It should be noted that, the quality of extracted local fractal map (in visually) caused to set the values in Figure 2, to the membership functions. Also,
these values could be changed based on the radiometric resolution of the input image.

![Membership functions for input variable DFD, AVE and VAR (b) Output variable (Size) with UC, PUC, PD and D membership functions [Novianto et al; 1999].](image)

The input parameters of the fuzzy set are: difference of fractal dimension (DFD), the average intensity difference (AVE) and variance difference (VAR) of two successive windows sizes at each position. The output is the optimum size of the window for the correspond position or pixel. We used six rules at this fuzzy set. For example, when the difference of average intensity is low, using of the current size is more probable. In other words, If AVE is low then Size=PUC.

The above variables are integrated by the fuzzy rules. First, a fuzzification process is applied to the variables DFD, AVE and VAR for fuzzy sets SMALL, LOW and HOMOGEN, respectively as shown in Figure 2. The defuzzification is performed using the centroid method. At the beginning, for each pixel the DFD, AVE and VAR are computed from difference of 11×11 and 9×9 window size. The estimated fractal dimension using the current size of the window (11×11) is selected if the centroid being in the UC range. Otherwise, decrease the size of window and repeat the above examination using 9×9 and 7×7 window size. If the centroid still does not be in the UC range, then decrease the size and repeat the above examination until the criterion is satisfied or it reaches the smallest size of the window.

So, according to the Figure 1, fractal dimensions of each band of Pauli image can be obtained using self-adaptive mowing window over the correspond band. Subsequently, the fractal feature vector can be computed using [5]. It should be noted that the values of the
fractal feature vector are normalized to [0,1]. Finally, to obtain the classification map, SVM as a prevailing classifier are applied to the proposed fractal vector. In the next section, there is a brief description about the SVM classifier.

**Support vector machines**

Support vector machines are a useful technique for data classification. Development of the classification system includes separating data into training and testing sets [Hsu et al., 2003]. Each instance in the training set contains features of the observed data and the class labels. In fact, SVM classify data with different class labels by determining a set of support vectors that outline a hyperplane in the feature space. It has been demonstrated that the optimal hyperplane which guarantees the best generalization performance is unique with the maximal margin of separation between the two classes. The term optimal separation hyperplane is used to refer to the decision boundary that minimizes misclassifications, obtained in the training step [Mountrakis et al.; 2010].

SVM are able to go beyond the limitations of linear learning machines by introducing the kernel function, which paves the way to find a nonlinear decision function. Kernel functions (e.g. Polynomial, RBF, Sigmoid) can handle the case samples are not linearly separable in the original space with map such input samples into a high dimensional feature space. Then, the SVM construct an optimal linear separating hyperplane in this higher dimensional space. The optimization problem is presented in [10] [Samadzadegan and Ferdosi, 2012].

\[
\begin{align*}
\text{Minimize} & : \frac{1}{2} \| w \|^2 + c \sum_{i=1}^{n} \xi_i \\
\text{Subject to} & : y_i (w.k(x) + b) \geq 1 - \xi_i
\end{align*}
\]

Where \( c \) is a regularization parameter and \( \xi_i \) (error variables) are used in order to deal with misclassified vectors, \( k \) is a kernel function, \( w \) and \( b \) are the parameters of the hyperplane, \( x \) and \( y \) are feature vector and class label, respectively. There are several kernel functions to project data to the higher dimension. In this study, Gaussian radial basis function [11] is used. More information about SVM can be found in Mountrakis et al. [2010] and Vapnik [1998].

**Experimental results**

In this section, two test images of an urban area (San Francisco Bay, CA, Fig. 3a) and an agricultural area (Flevoland in the Netherlands, Fig. 3b), both acquired by the NASA/Jet Propulsion Laboratory’s Airborne SAR (AIRSAR) at L-band, are chosen for performance valuation of the proposed method. Both data sets have been widely used in the polarimetric SAR literature over the last two decades and publicly available through the polarimetric SAR data processing and educational tool (PolSARpro) by ESA. Figure 3 shows the Pauli color coded images of the San Francisco Bay and Flevoland with \(|hh-vv|\), \(|2hv|\), and \(|hh+vv|\), for the three composite colors red, green, and blue, respectively. It is worth mentioning that in this study to retain the resolution and to preserve the texture information, the fractal feature vector is generated from the Pauli vector before despeckling. Since the original AIRSAR images are pre-processed without speckle reduction, the quality of a classification
map can also indicate its resistance to the speckle effect.

The first test site’s (San Francisco Bay) image mainly contains three types of land covers, which are urban, ocean and vegetation areas. Fractal feature vector using self-adaptive window approach is computed from the Pauli vector of the San Francisco Bay data set. To test the performance of the proposed vector and compare its classification results with Pauli decomposed vector, SVM with the same training and testing areas for the three classes as well as the same parameters (like regularization parameter, kernel function and so on) are applied to them. Table 1 presents the training and testing samples which are manually selected. Since SVM are good at the small training sets classification, generally 1127 pixels are chosen for algorithm training.

| Class   | Training | Testing |
|---------|----------|---------|
| Urban   | 288      | 4040    |
| Vegetation | 498      | 3514    |
| Ocean   | 341      | 4897    |

To reveal the effect of window size in the proposed contextual classification, the fractal feature vector is computed with fixed window sizes (5-11) as well as the self-adaptive window (fuzzy) approach. Figure 4, shows the classification maps obtained by applying SVM to the Pauli and fractal feature vectors. White, gray and black pixels in the classification images are correspond to the urban, vegetation and ocean areas, respectively. As can be seen, classification based on the Pauli decomposed vector alone does not provide sufficient sensitivity for the separation of vegetation and ocean classes (Fig. 4a). However, the results of fractal vectors in Figures 4b-f strongly highlight the efficiencies of the proposed feature vector. The main factor in the computation of fractal feature vector is the size of the moving window.
window. Large windows are appropriate for the smooth areas and smaller windows for the rough areas. It is understood that smaller window size does not cover sufficient spatial/texture information to characterize land use types. However, if the window size is too large, too much information from other land use/cover types could be included and hence the algorithm may not be effective. Figures 4b-e show the effect of window size in classification results using the fractal feature vector.

Figure 4 - Classification results for the San Francisco Bay image by applying SVM to the Pauli and fractal vectors.
Table 2 presents the quantitative comparison of the obtained results by the kappa coefficient. Using of fractal dimension as a texture improves the accuracy of the classification from 68.82% in Pauli vector to the 84.48% in the proposed feature vector with the self-adaptive window. Nevertheless, as can be seen in Figure 4b and c, the vegetation and urban classes are not properly separated. This is related to using of inappropriate window sizes (5 and 7) at the entire of the image. Also, mixed boundary pixels or features problems due to large window size can be seen in Figure 4e. However, it seems that these problems are addressed using self-adaptive window approach. Figure 5 shows the number of different window sizes that have been used to compute the fractal feature vector using the self-adaptive window approach in San Francisco image.

![Figure 5 - Histogram of different window size in self-adaptive approach.](image)

In the next experiment, the second data set (Flevoland image) is classified to the eight different classes as the number of classes in the ground truth and the same number that Yu and Qin [2012] used to segment the image. The ground truth image of the second test site is shown in Figure 6d. Training samples (5039 pixels) are selected from the ground truth image and shown in Figure 6c, also, the testing samples (58312 pixels) are the same as the ground truth image pixels without considering the training pixels. Classification maps in the same manner as above experiment are obtained from the Pauli and fractal feature vectors (Figs.6a-b). Fractal dimensions are computed using the self-adaptive window approach. Table 3, presents the confusion matrixes of the classification results. According to the confusion matrix, the value of the kappa coefficient for the proposed
contextual classification (89.48%) is more considerable than 70.03% for the classification map using the Pauli decomposed vector. From Figure 6a and b, it can apparently observe that using fractal feature vector instead of decomposed Pauli vector has led to more accurate classification map because the confusion between classes using the proposed feature vector is far less than the Pauli vector. As can be seen from the Table 3, the number of correctly classified pixels for the classes barely, wheat, water, beet, rapeseed and bare soil in the proposed contextual classification is more than the classification map using the Pauli decomposed vector. However, classes potato and Lucerne are more correctly classified using the Pauli vector than the fractal vector. This classification error in the contextual classification can be compensated using more training data of potato and Lucerne classes.

Figure 6 - Classification results for the Flevoland image by applying SVM to the Pauli and fractal vectors.
Table 3 - Confusion matrix for the classification maps of Flevoland obtained by applying SVM to the Pauli and self-adaptive fractal vectors.

| True class | Result of Pauli decomposed vector | Result of fractal feature vector |
|------------|-----------------------------------|---------------------------------|
| Barely     | 6504 109 0 0 0 35 1386 358        | 6744 20 0 0 0 0 126 390         |
| Wheat      | 143 12239 18 76 0 3384 320 195    | 0 14858 9 50 2 336 0 246        |
| Water      | 0 34 5301 1141 633 304 0 0         | 0 5 6214 890 665 73 0 0          |
| Beet       | 10 193 858 3872 239 529 0 0        | 0 1 193 4370 250 6 0 0           |
| Potato     | 0 0 177 415 4725 0 0 0             | 0 0 0 246 4675 0 0 0             |
| Rapeseed   | 6 2719 66 78 2 6779 5 0            | 0 310 4 27 7 10565 0 0           |
| Bare soil  | 393 9 0 0 0 7 3529 29              | 369 11 0 0 0 55 5114 12          |
| Lucerne    | 57 752 0 6 0 2 0 961               | 0 850 0 5 0 5 0 895              |

Nevertheless, in general, dramatic improvement is obtained using fractal feature vector in comparison to the Pauli decomposed vector. Lucerne and potato remain problematic, but accuracy of other classes significantly improved using the contextual classification. Speckle noise is the main problem in the classification of polarimetric SAR data, which plays a vital role in information extraction and classification. Due to speckle, it is difficult to classify the PolSAR image based on the pixel values because speckle makes various pixels to be mixed and hence provides an ambiguous classification [Henderson and Lewis, 1998]. To disclose the effect of speckle in the contextual classification, the Pauli decomposed
vector is refined using enhanced Lee filter [Lopes et al., 1990] with size of 5×5 window. In this case, the fractal feature vector is constructed using the refined Pauli vector and local fractal maps (with self-adaptive approach), which obtained in the previous experiments from the original data. Figure 7 shows the classification results for San Francisco Bay and Flevoland areas obtained by applying SVM to the refined Pauli and fractal vectors. Table 4 presents the quantitative comparison of the classification maps.

According to Tables 2 and 4, by applying enhanced Lee filter, the accuracy (kappa coefficient) of the contextual classification in San Francisco Bay and Flevoland images improved from 84.48% to 87.81% and 89.48% to 91.62%, respectively, in other words, speckle effect in these images are 3.33% and 2.14%, respectively. However, speckle has more effect in the Pauli vector (12.17% and 11.89% for San Francisco Bay and Flevoland, correspondingly). According to Tzeng et al. [2007], speckle can be modeled in the spatial chaotic system and characterized by its fractal dimension. Accordingly, speckle is modeled properly in the proposed fractal feature vector and its effect is minimized.

![Classification results for refined data of San Francisco Bay and Flevoland using enhanced Lee filter.](image)

ITESM, Mexico
Table 4 - Performance comparison (in percent) for refined data using enhanced Lee filter.

| Data Sets     | Applying SVM         | Kappa coefficient | Overall accuracy |
|---------------|----------------------|-------------------|-----------------|
| San Francisco Bay | Pauli vector        | 80.99             | 87.43           |
|                | Self-adaptive fractal vector | 87.81             | 91.92           |
| Flevoland     | Pauli vector        | 81.92             | 84.88           |
|                | Self-adaptive fractal vector | 91.62             | 92.97           |

Conclusion
This paper has presented a fractal based feature vector for classification of the polarimetric SAR images. The proposed feature vector has been constructed from the Pauli decomposed vector and its fractal dimensions. For each element of the Pauli decomposed vector, a local fractal map that provides a textured image is computed using the wavelet analysis. Using of texture information in addition to the polarimetric data provided more efficient sensitivity for the separation of some classes in comparison with the case of using alone polarimetric data. Support vector machines due to their ability to handle the nonlinear classifier problem have been applied to the proposed vector. The overall classification accuracies and qualitative classification maps for the San Francisco Bay and Flevoland data sets demonstrate the effectiveness of the proposed classification framework. Experiments showed promising results, despite the presence of speckle. Speckle has modeled properly in the proposed fractal feature vector and its effect is minimized. Based on the experimental results using real polarimetric SAR data, the proposed feature vector performs well compared to the Pauli decomposed vector, however, more experiments using data of the different polarimetric imagery should be done for a general conclusion.

The main factor in the computation of in the fractal feature vector is the size of moving window. Large windows are appropriate for the smooth areas and smaller windows for the rough areas. Accordingly, in this paper a self-adaptive window approach based on the fuzzy logic has been implemented to select the optimum size of the window in different areas of the image. The problem with using of fixed window size over the entire of image is: the small window does not cover sufficient spatial/texture information to characterize land use types and large window could be included information from other land use/cover types. However, our experiment showed the effectiveness of self-adaptive window approach in comparison to the case using of fixed window size over the entire of the image.

References
Aghababaee H., Tzeng Y.C., Amini J. (2012) - *Swarm intelligence and fractals in dual-pol synthetic aperture radar image change detection*. SPIE Journal of Applied Remote Sensing, vol. 6 (1): 063596. doi: http://dx.doi.org/10.1117/1.JRS.6.063596.

Beaulieu J.M., Touzi R. (2004) - *Segmentation of textured polarimetric SAR scenes by likelihood approximation*. IEEE Transactions on Geoscience and Remote Sensing, 42 (10): 2063-2072. doi: http://dx.doi.org/10.1109/TGRS.2004.835302.

Betti A., Barni M., Mecocci A. (1997) - *Using a wavelet-based fractal feature to improve texture discrimination on SAR images*. IEEE International Conference on Image Processing, 1: 251-254. doi: http://dx.doi.org/10.1109/ICIP.1997.647752.
Cloude S.R., Pottier E. (1997) - *An entropy based classification scheme for land applications of polarimetric SAR*. IEEE Transaction on Geoscience and Remote Sensing, 35 (1): 68-78. doi: http://dx.doi.org/10.1109/36.551935.

Goodman J. (1976) - *Some fundamental properties of speckle*. Journal of Optical Society of America, 66 (11): 1145-1150. doi: http://dx.doi.org/10.1364/JOSA.66.001145.

Goumehei E., Tolpekin V.A. (2011) - *Contextual image classification with support vector machines*. Proceeding of 1th International conference on sensor and models in photogrammetry and remote sensing (SPMR), Tehran, Iran.

Henderson F.M., Lewis A.J. (1998) - *Principles and Applications of Imaging Radar*. Manual of Remote Sensing. Third Edition, Volume 2, ASPRS, John Wiley and Sons Inc., Toronto.

Hsu C.W., Chang C.C., Lin C.J. (2003) - *A practical guide to support vector classification*. Department of Computer Science and Information Engineering, National Taiwan University.

Huang C., Davis L.S., Townshend J.R.G. (2002) - *An assessment of support vector machines for land cover classification*. International Journal of Remote Sensing, 23 (4): 725-749. doi: http://dx.doi.org/10.1080/01431160110040323.

Kourgli A., Oukil Y., Hirche A., Ouarzeddine M. (2011) - *Polarimetric SAR images segmentation incorporating texture features*. IEEE 17th International Conference on Digital Signal Processing (DSP), pp 1-5. doi: http://dx.doi.org/10.1109/ICDSP.2011.6004979.

Liu M., Zhang H., Wang C. (2011) - *Applying the log-cumulants of texture parameter to fully polarimetric SAR classification using Support Vector Machines Classifier*. IEEE CIE International Conference on Radar, 1: 728-731. doi: http://dx.doi.org/10.1109/CIE-Radar.2011.6159644.

Lopes A., Touzi R., Nezry E. (1990) - *Adaptive speckle filters and Scene heterogeneity*. IEEE Transaction on Geoscience and Remote Sensing, 28 (6): 992-1000. doi: http://dx.doi.org/10.1109/36.62623.

Mandelbrot B.B., Van Ness J.W. (1968) - *Fractional Brownian motions, fractional noises and applications*. SIAM Review, 10 (4): 422-437. doi: http://dx.doi.org/10.1137/1011093

Mcdonald M.K., Varadan V., Leung H. (2002) - *Chaotic behavior and non-linear prediction of airborne radar sea clutter data*. IEEE International conference of Radar, pp. 331-337. doi: http://dx.doi.org/10.1109/NRC.2002.999740.

Melgani F., Bruzzone L. (2004) - *Classification of hyperspectral remote sensing images with support vector machines*. IEEE Transactions on Geoscience and Remote Sensing, 42 (8): 1778-1790. doi: http://dx.doi.org/10.1109/TGRS.2004.831865.

Mountrakis G., Jungho I., Ogole C. (2010) - *Support vector machines in remote sensing: a review*. ISPRS Journal of Photogrammetry and Remote Sensing, 66 (3): 247-259. doi: http://dx.doi.org/10.1016/j.isprsjprs.2010.11.001.

Novianto S., Guimaraes L., Suzuki Y., Maeda J., Anh V.V. (1999) - *Multi-windowed Approach to the optimum Estimation of the Local Fractal Dimension for Natural Image Segmentation*. IEEE international conference on Image Processing, 3: 222-226. doi: http://dx.doi.org/10.1109/ICIP.1999.817105.

Pal M., Mathur P.M. (2005) - *Support vector machines for classification in remote sensing*. International Journal of Remote Sensing, 26 (5): 1007-1011. doi: http://dx.doi.org/10.1080/01431160512331314083.

Pant T., Singh D., Srivastava T. (2010) - *Advanced fractal approach for unsupervised
classification of SAR images. Elsevier Advances in Space Research, 45: 1338-1349. doi: http://dx.doi.org/10.1016/j.asr.2010.01.008.

Parra C., Iftekharuddin. K., Rendon D. (2003) - Wavelet Based Estimation of the Fractal Dimension in fBm Images. IEEE International conference on neural engineering, Capri Island, Italy, pp 533-536. doi: http://dx.doi.org/10.1109/CNE.2003.1196881.

Rodionova N.V. (2007) - A combined use of decomposition and texture for terrain classification of fully polarimetric SAR images. Workshop of POLinSAR, 22-26 January, ESAESRIN, Frascati, Italy.

Samadzadegan F., Ferdosi E. (2012) - Classification of Polarimetric SAR Images Based on Optimum SVMs Classifier Using Bees Algorithm. International Conference on Intelligent Computational Systems (ICICS), Dubai, UAE.

Touzi R. (2007) - Target scattering decomposition in terms of Roll-Invariant target parameters. IEEE transaction on Geoscience and Remote Sensing, 45 (1): 73-84. doi: http://dx.doi.org/10.1109/TGRS.2006.886176.

Tso B., Mathur P.M. (2009) - Classification methods for remotely sensed data. Second edition. CRC Press, Boca Raton, FL. doi: http://dx.doi.org/10.1201/9781420090741.

Tzeng Y.C, Chiu S.H., Chen K.S. (2007) - Change Detections from SAR Images for Damage Estimation Based on a Spatial Chaotic Model. IEEE International conference on Geoscience and Remote Sensing Symposium, Barcelona, Spain, pp. 1926-1930. doi: http://dx.doi.org/10.1109/IGARSS.2007.4423203.

Van Zyl J.J. (1989) - Unsupervised classification of scattering mechanisms using radar polarimetry data. IEEE Transaction on Geoscience and Remote Sensing, 27 (1): 36-45. doi: http://dx.doi.org/10.1109/APSAR.2009.5374123.

Vapnik V. (1998) - Statistical learning theory. New York: John Wiley and Sons Inc.

Wu D., Linders J. (1999) - A new texture approach to discrimination of forest clear cut, canopy, and burned area using airborne C-band SAR. IEEE Transaction on Geoscience and Remote Sensing, 37 (1): 555-563. doi: http://dx.doi.org/10.1109/36.739113.

Yu P., Qin A.K. (2012) - Unsupervised polarimetric SAR image segmentation and classification using region growing with edge penalty. IEEE Transaction on Geoscience and Remote Sensing, 50 (4): 1302-1317. doi: 10.1109/TGRS.2011.2164085.

Zhang L., Zou B., Zhang J., Zhang Y. (2010) - Classification of polarimetric SAR image based on support vector machine using multiple-component scattering model and texture features. Eurasip Journal on Advances in Signal processing. Hindawi.

Zhou G., Cui Y., Chen Y., Yin J., Yang J., Su Y. (2010) - Pol-SAR images classification using texture features and the complex Wishart distribution. IEEE Radar Conference, pp. 491- 494. doi: http://dx.doi.org/10.1109/RADAR.2010.5494572.

Received 01/06/2012, accepted 04/12/2012