SAR Segmentation using Anisotropic Diffusion

Sathit Intajag Non-member (Faculty of Engineering, KMITL, kisathit@kmit.ac.th)
Vittaya Tipsuwanporn Non-member (Faculty of Engineering, KMITL, ktvittay@kmit.ac.th)
Fusak Cheevasuwit Non-member (Faculty of Engineering, KMITL, kcfusak@kmit.ac.th)

Keywords: SAR segmentation, speckle noise, anisotropic diffusion, ENL

Speckle effects are commonly observed in synthetic aperture radar (SAR) image, which applies in many applications, such as agriculture and forestry. The human eye is capable of deriving meaningful information from SAR images; however, an automatic or semi-automatic processing algorithm has difficulty distinguishing the objects in the images because of noise effects present in those images. This paper presents a segmentation method for SAR images, which employs an anisotropic diffusion algorithm.

In our technique, anisotropic diffusion method has been developed to achieve a good trade-off between noise removal and boundary region preservation. Generally, the anisotropic diffusion model is formulated to eliminate additive noise. Speckle noise is multiplicative in nature; however, the multiplicative noise may be transformed to the additive noise by a logarithmic function. The diffusivity value of the diffusion process uses a structure tensor in order to discriminate textures. When the image regions have the same textures, they are grown and bounded by a diffusion mechanism. The proposed segmentation method is the same as region growing but without marker set or seeds. On the other hand, our diffusion algorithm can stop the iteration process by a standard deviation to mean criteria, which is provided according to the homogeneity criterion. Figure 1 illustrates our SAR segmentation algorithm.

The performance of the proposed algorithm is assessed with both quantitative comparison and visual judgment. Figure 2 shows comparison results of the proposed algorithm with the fuzzy c-Means and Zaart's method. In Fig. 2, the synthetic image is added with the speckle noise by varying the look numbers from 4 to 16 to assert the accuracy and homogeneity in each region. Fig. 2(a) illustrates RUMA values, which our algorithm has misclassification rate lower than the fuzzy c-Means and Zaart’s method. Fig. 2(b) depicts the ability of the segmentation algorithms that can estimate the radar cross section or mean values of the segmented image, which are measured on homogeneity index $U$. Fig. 3 illustrates the segmented results with $R = 40$, the iteration numbers of ERS-1 and JERS-1 equal 29,600 and 38,235, respectively.

The proposed algorithm is a semi-automatic method that can estimate the mean of each region when a user provides the rectangular coordinate and $R$ value. Homogenous regions are grown by increasing $R$ value, which should be declared corresponding with a number of objects in input image. On the other hand, the proposed method can estimate the class numbers in an image underlying the $R$ value in the rectangular coordinate. The higher the value of $R$ is, the lower the number of classes.
SAR Segmentation using Anisotropic Diffusion

Sathit Intajag* Non-member
Vittaya Tipsuwanporn* Non-member
Fusak Cheevasuwit* Non-member

Speckle effects are commonly observed in synthetic aperture radar (SAR) images. The human eye is capable of deriving meaningful information from SAR images; however, an automatic or semi-automatic processing algorithm has difficulty in distinguishing objects in the images because of noise effects present in those images. This paper presents a segmentation method for SAR images, which employs an anisotropic diffusion algorithm. In the proposed scheme, a SAR image is transformed into a logarithmic domain where the diffusion process is used to grow homogeneous regions in the noise environment until the regions reach some criteria for homogeneity; consequently, the segmented image in the logarithm domain is converted to the intensity domain by an exponential function. To grow homogeneous regions the adaptive diffusion method is introduced with a tensor technique in which tensor data are varied with the neighboring pixels. The diffusion algorithm will stop itself by a standard deviation divided by the mean, which is provided according to the homogeneity criteria. Results are shown on both synthetic and satellite SAR images. The evaluation of the proposed method employs the theoretical gain of equivalent numbers of looks (ENL).

Keywords: SAR segmentation, speckle noise, anisotropic diffusion, ENL

1. Introduction

Many land applications of SAR images (1) (2), such as agriculture or forestry, use information from intensity data. The accuracy of these applications requires methods for identifying changes between images gathered at different times or with a single set of images at a single time, in which preprocessing to reduce speckle is an essential step. Due to the image noise by coherent effects, the overlapping of signatures of various land categories, and the strong effect of the local topography, even forest mapping turns out to be very difficult.

Typically, when it comes to filtering speckle noise, a spatial domain and many spatial filters are provided as described by Oliver and Quegan (3). However, the anisotropic diffusion method has been developed to achieve a good trade-off between noise removal and boundary region preservation. Generally, the anisotropic diffusion model is formulated to eliminate additive noise. Speckle noise is multiplicative in nature; however, the multiplicative noise can be transformed to additive noise by a logarithmic function (4) (5). Furthermore, the proposed method modifies the diffusion process (6) for filtering the speckle noise by using the standard deviation divided by mean criteria to stop the iteration process.

The proposed scheme is a region-based segmentation algorithm. Region-based segmentation methods postulate that neighboring pixels within the same region have similar intensity values, of which the split-and-merge (7) technique is probably the most well known. The general procedure is to compare a pixel with its immediate surrounding neighbors. If a criterion of homogeneity is satisfied, the pixel can be classified into the same class as one or more of its neighbors. In order to achieve success in the segmentation method choosing the criteria for homogeneity is of the utmost importance.

Using anisotropic diffusion to segment an image is usually embedded with another mechanism such as watershed transformation (8) and thresholding technique (9). In this paper, anisotropic diffusion is employed to segment SAR images in the logarithm domain. The diffusivity value of the diffusion process uses a structure tensor in order to discriminate textures. When the image regions have the same textures, they are grown and bounded by a diffusion mechanism. This segmentation method is the same as region growing but without a marker set or seeds. On the other hand, our diffusion algorithm can stop the iteration process within a standard deviation divided by mean criteria, which is provided according to the homogeneity criterion.

Section 2 presents the handling of backgrounds by the proposed method that consists of speckle noise modeling, anisotropic diffusion, diffusion tensor, and region growing. Section 3 describes the method of enhancing the SAR images in a logarithm domain. The experimental results of the despeckled images are given in section 4. The implications of these results are discussed in section 5 and the final section is our conclusion.

2. Related Works

2.1 Speckle Modeling

Generally, speckle noise is modeled with intensity and amplitude formats. The
The proposed method works on intensity data, which is transformed to a logarithm domain. The intensity of a SAR image \(F_L(x, y)\) at a pixel coordinate \((x, y)\), where the SAR image is assumed as the average of \(L\) looks, can be expressed by

\[
F_L(x, y) = I(x, y)R_L(x, y)
\]  

where \(R_L\) is the speckle noise with \(L\) looks and \(I\) represents the radius cross section of the imaged surface (\(^{10}\)).

The multiplicative model of speckle noise suggests performing a logarithmic transformation on the equation (1), giving

\[
\tilde{F}_L = I + \tilde{R}_L
\]

where \(\tilde{F}_L = ln(F_L)\), \(\tilde{I} = ln(I)\) and \(\tilde{R}_L = ln(R_L)\). From the transformation, \(\tilde{R}_L\) becomes stationary white noise, we get the additive noise model, \(\tilde{F}_L\) (\(^{4}\) (\(^{5}\)).

An equivalent number of looks or ENL (\(^{10}\)) is often used to estimate the speckle noise level in a SAR image, which is formulated by the ratio of mean to variation in the homogeneous image area as given by:

\[
ENL = E(F)^2/V(F)
\]

where \(E(F)\) and \(V(F)\) denote the mean and variance that are estimated from the homogeneous area, respectively. In our scheme, ENL is employed to measure the degree of speckle reduction, by the meaning of: the higher the ENL value, the stronger the speckle noise reduction.

### 2.2 Anisotropic Diffusion

Anisotropic diffusion is derived for nonlinear diffusion. It was first proposed and has attracted much deserved attention in the field of image processing by Perona and Malik (\(^{11}\)). In their work, nonlinear diffusion was used to reduce noise while enhancing the true location of edge images. This diffusion is introduced with a space- and time-variant diffusion coefficient, \(c(x, y, t)\), as formulated by

\[
\frac{\partial f(x, y, t)}{\partial t} = \text{div} (c(x, y, t) \cdot \nabla f(x, y))
\]

where \(f(x, y, t)\) is an image pixel value at discrete time steps (\(t^th\) iterations, for \(t = 0\) the representation is the original data: \(f(x, y, 0) = f(x, y)\)). \(\text{div}\) is the divergence operator and \(\nabla f(x, y)\) denotes the gradient of images.

To allow the diffusion process to run smoothly from intra-region to inter-region and thus preserve edges, the region boundaries need to be identified. Obviously, the boundaries are not available \(a\ pri\ or\), and the best way to estimate the boundary locations is by using an edge detector. Perona and Malik (\(^{11}\)) claimed that the simplest gradient of images at time \(t\) (\(\nabla f(x, y, t)\)) works excellently; consequently, the diffusion coefficient, \(c(x, y, t)\), is given by:

\[
c(x, y, t) = g(|\nabla f(x, y, t)|)
\]

The diffusivity function \(g(|\nabla f(x, y, t)|)\) is provided to enhance the edges of objects in an image by smoothing the original image while preserving brightness discontinuities. Perona and Malik (\(^{11}\)) defines the function as

\[
g(|\nabla f(x, y, t)|) = \left(1 + \frac{|\nabla f(x, y, t)|^2}{K^2}\right)^{-1}
\]

where \(K\) denotes a parameter controlling the diffusion strength. The enhancing process is obtained by gradient magnitude \(|\nabla f(x, y, t)|\): if \(|\nabla f(x, y, t)|\) is large, then the diffusion will be low to preserve the edges. If \(|\nabla f(x, y, t)|\) is small, then the diffusion will tend to smooth the pixel \(f(x, y)\).

Catté et al. (\(^{12}\)) used a Gaussian function \((G_\sigma)\) with a small variance for convolution with the gradient magnitude term by replacing \(g(|\nabla f(x, y, t)|)\) with \(g(G_\sigma \ast |\nabla f(x, y, t)|)\). The regulation of Catté et al. (\(^{12}\)) provides edge sharpening and is more stable than the Perona and Malik method. From the Perona and Malik method, Weickert and Benhamouda (\(^{13}\)) studied in more detail about the discrete implementations, a regularization factor.

### 2.3 Diffusion Tensor

Diffusion tensor is a technique used to develop a directed diffusion by employing local geometric structures. It is adapted from coherence enhancing diffusion (CED) proposed by J. Weickert in 1999 (\(^{10}\)). He suggested many useful properties of nonlinear diffusion under some general assumptions, which concern the input images and some conditions imposed on the diffusion tensor, \(D\), which was used to replace the diffusion coefficient, \(c(x, y, t)\). A formulation of the CED equation is expressed by:

\[
\frac{\partial f(x, y, t)}{\partial t} = \text{div} (D \cdot \nabla f(x, y))
\]

The diffusivity tensor is a function of the image gradient, where \(D\) is defined in a matrix framework as follows.

\[
D = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}
\]

This matrix is constructed by the smoothing perpendicular (\(^{14}\)) of the image gradient and an integration scale \(\rho\) by using the convolution of an image \(f(x, y)\) with a Gaussian kernel \(G_\sigma\) to obtain a smoothed version of the image with standard deviation \(\sigma, f_\sigma(x, y) = G_\sigma \ast f(x, y)\), where \(\ast\) represents the convolution operator. Accordingly, the diffusivity tensor can be attained by a componentwise convolution of terms \(\nabla f_\sigma(x, y)(\nabla f_\sigma(x, y))^T\), which are partial derivatives, and a Gaussian \(G_\rho\) that is given as:

\[
S_\rho(\nabla f_\sigma(x, y)) = G_\rho \ast (\nabla f_\sigma(x, y)(\nabla f_\sigma(x, y))^T)
\]

where \(T\) denotes a transposition of matrix. The structure tensor, \(S_\rho\), is symmetric and positive semi-definite.

\[
S_\rho = \begin{bmatrix} s_{11} & s_{12} \\ s_{21} & s_{22} \end{bmatrix}
\]

In the CED (\(^{10}\)), an integration scale \(\rho\) takes positive values. The diffusion process along coherent structures is based on the construction of a diffusion tensor whose eigen-directions coincide with the eigenvectors of the structure tensor and provide the different eigenvalues; namely,
where \( \mu \) is the mean, \( \sigma \) the standard deviation, and \( C \) the variance. Thus, the homogeneity criterion has a threshold value \( T \) which is used to define \( \lambda_2 \).

The CED method based on the structure tensor provides a local description for boosting up the ridges and valleys, which is effective for enhancing images such as a fingerprint or a blood vessel. In this paper, this diffusion method is modified to remove the speckle noise by preserving the information detail.

### 2.4 Region Growing

The region growing algorithm is based on the growth of a region whenever its interior is homogeneous according to certain features such as intensity, or texture. The implemented algorithm follows the strategy of typical region growing: it is based on the growth of a region by adding similar neighbors. The most traditional implementation starts by choosing a starting point called a seed pixel. Then, the region grows by adding similar neighboring pixels according to a certain homogeneity criterion, by increasing gradually the size of the region. Thus, the homogeneity criterion has a function of deciding whether a pixel belongs to the growing region or not. The decision of merging is generally decided based only on the contrast between the evaluated pixel and the region.

However, it is not easy to decide in the region growing when the difference is small (or large) enough to make a decision. The edge map provides an additional criterion in this situation, such as the condition of contour pixels, when deciding to aggregate it. The encounter of a contour signifies that the process of growing has reached the boundary of the region, so the pixel must not be aggregated and the growth of the region is finished.

We propose a region-based segmentation method similar to region growing, except that seed pixels are not necessary. Therefore, the proposed method can achieve semi-automatic segmentation along with the addition of the homogeneity criterion of the standard deviation divided by mean.

### 3. Segmentation by Anisotropic Diffusion

To reduce the speckle noise by anisotropic diffusion, the proposed method uses logarithmic transformation to convert the multiplicative noise to additive noise. In practice, we employ a natural logarithm by adding the image data with 1 for convenience in calculation. The SAR image in an additive model as seen in Eq. (2) is an optimal model to process with the anisotropic diffusion methods. After the noise is smoothed out by the diffusion process, the image data is converted to the intensity domain by an exponential function.

The anisotropic diffusion, which is used to smooth out the noise, is modeled by Eq. (7) when the diffusivity tensor \( D \) is modified to reduce speckle noise in the logarithmic domain and to discriminate textures in each region. In modification, the diffusion coefficient is constructed along boundaries of the homogeneous areas by using a local gradient of the smoothed image \( f_{\sigma}(x, y) \). Generally, the Gaussian smoothing used for the structure tensor dislocates the edges in feature space leading to inaccurate segmentation results. However, a nonlinear structure tensor based on a nonlinear matrix-valued diffusion method can tackle these dislocations.

The diffusion tensor \( D \) is decomposed as

\[
D = \begin{bmatrix}
  d_{11} & d_{12} \\
  d_{21} & d_{22}
\end{bmatrix} = V \begin{bmatrix}
  \lambda_1 & 0 \\
  0 & \lambda_2
\end{bmatrix} V^T, \quad \lambda_1, \lambda_2 \geq 0
\]

where the parameters: \( \lambda_1 \) and \( \lambda_2 \) are conductivity values and \( V \) denotes the rotation matrix. These parameters are calculated by a first-order derivative in the neighborhood of a coordinate pixel \((x, y)\). In the proposed scheme, \( \lambda_1 \) and \( \lambda_2 \) represent conductivity of the gradient, expressed as

\[
\lambda_1 = \frac{\|\nabla f_\sigma\|^2}{K},
\]

\[
\lambda_2 = e^{-\frac{\|\nabla f_\sigma\|^2}{K}},
\]

\[
\lambda_1 = 0.2\lambda_2
\]
method uses the homogeneity index, 
the problem of partitioning each region. The proposed 
mentation methods. This comparison concentrates on 
input data by taking logarithm. A user identifies a ho-
mogeneous region of the input data in rectangular co-
doordinates and defines a homogeneity criterion \( R \). The 
algorithm will calculate the standard to mean ratio, \( C_0 \), 
and go to the step of initialization of anisotropic dif-
usion parameters. Consequently, the diffusion process 
and measuring the homogeneity region will be started 
and operated until the ratio \( C_0/C_t \) is greater than the 
defined value \( R \), and then the iteration processes are 
finished.

4. Experiments and Results

The performance of the proposed algorithm is assessed 
with both quantitative comparison and visual judgment. 
The major purpose of the algorithm is to segment SAR 
images; however, tests on simulated data are also in-
structive to guarantee that the image being tested meets 
the conditions assumed by the algorithms. In the simu-
lation process, a synthetic image is provided with struc-
tural features and brightness variations as similar as pos-
sible to a real image. To evaluate the accuracy of the 
algorithm, the synthetic image with speckle noise is cre-
ated and tested by quantitative comparison using the 
second algorithm fuzzy c-Means of Jawahar et al.\(^{(20)}\) 
and SAR segmentation of Zaart et al.\(^{(21)}\). For visual 
judgment, ERS-1 and JERS-1 images are employed to 
test the proposed algorithm.

The reasons that use the fuzzy c-Means and the al-
gorithm of Zaart et al. for comparing with our method are:

\begin{itemize}
  \item Fuzzy c-Means is a standard algorithm for segmen-
tation and classification,
  \item The algorithm of Zaart et al. is unsupervised that 
  uses inflection points from extreme points of first 
  derivative of image histogram for declaration the 
  number of classes.
\end{itemize}

4.1 Quantitative Comparison

For the quan-
titative assessment, both homogeneity indexes, \( U \), and 
Relative Ultimate Measurement Accuracy (\( RUMA \))\(^{(22)}\) 
\(^{(23)}\) are useful tools in comparing the performance of seg-
mentation methods. This comparison concentrates on 
the problem of partitioning each region. The proposed 
method uses the homogeneity index, \( U \), to measure the 
former by dividing an input image with the segmenta-
tion algorithm. The homogeneity index is given by 
integrating the normalized intra-region uniformity val-
ues\(^{(23)}\). The uniformity of a feature over a region can 
be computed on the basis of the variance of that feature 
evaluated at every pixel belonging to that region. In 
picular, for a grey-level image \( f(x, y) \), let \( R_i \) be the 
ith segmented region, \( A_i \) be the area of \( R_i \), and \( U \) be 
the normalized intra-region uniformity of the \( M \) classes,

\[
U = 1 - \frac{\sum_{i=1}^{M} \sum_{(x,y) \in R_i} (f(x,y) - \mu_{A_i})^2}{C} \\
\mu_{A_i} = \frac{1}{A_i} \sum_{(x,y) \in R_i} f(x,y),
\]

where \( C \) denotes the normalization factor. In the pro-
posed scheme, factor \( C \) is obtained from the variance of 
the intensity. The term \( \mu_{A_i} \) is an expected value of the 
ith region of segmentation methods. If all the regions are 
homegeneous, then the expected values and corresponding 
variances of \( U \), are easily interpreted. The nearer \( U \) 
is to 1, the better the homegeneity is within classes.

\( RUMA \) is used to assess misclassification and object 
area error rate of a segmentation algorithm, obtained 
from the segmented image in comparison with the ref-
ence image. It provides useful discrepancy measures, 
which is defined as:

\[
RUMA = \frac{|R_f - S_f|}{R_f} \times 100\%,
\]

where \( R_f \) denotes the feature values of the reference im-
age and \( S_f \) denotes the feature values measured from 
the segmented image. \( RUMA \) index represents the 
processing accuracy. The lower index value indicates both 
a better quality of segmented images and a better per-
formance of the algorithms.

In verification of the misclassification rate, ground 
truth or reference data can be used for assessing the al-
gorithm to evaluate the accuracy results. The synthetic 
image results of our proposed algorithm, the fuzzy c-
Means\(^{(20)}\) and the algorithm of Zaart et al.\(^{(21)}\) are com-
pared and shown in Fig. 2. The fuzzy c-Means algo-
Table 1. The numerical results from synthetic image

<table>
<thead>
<tr>
<th>L</th>
<th>SNR(dB) Before</th>
<th>ENL Before</th>
<th>Iterations</th>
<th>U</th>
<th>RUMA(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>1.25</td>
<td>4.61</td>
<td>2.92</td>
<td>28.68</td>
<td>185114</td>
</tr>
<tr>
<td>6</td>
<td>2.82</td>
<td>6.72</td>
<td>5.93</td>
<td>42.74</td>
<td>128563</td>
</tr>
<tr>
<td>8</td>
<td>3.70</td>
<td>6.79</td>
<td>7.87</td>
<td>46.60</td>
<td>30790</td>
</tr>
<tr>
<td>10</td>
<td>4.61</td>
<td>7.73</td>
<td>9.92</td>
<td>71.87</td>
<td>16917</td>
</tr>
<tr>
<td>12</td>
<td>5.30</td>
<td>8.35</td>
<td>11.46</td>
<td>105.30</td>
<td>13297</td>
</tr>
<tr>
<td>14</td>
<td>5.91</td>
<td>8.65</td>
<td>13.76</td>
<td>145.95</td>
<td>7732</td>
</tr>
<tr>
<td>16</td>
<td>6.38</td>
<td>8.96</td>
<td>16.09</td>
<td>247.57</td>
<td>1660</td>
</tr>
</tbody>
</table>

Table 2. The numerical results from ERS-1 image

<table>
<thead>
<tr>
<th>R</th>
<th>Iterations</th>
<th>Mean Variance</th>
<th>U</th>
<th>ENL</th>
<th>No. of Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>244</td>
<td>22.48</td>
<td>1.21</td>
<td>416.38</td>
<td>10</td>
</tr>
<tr>
<td>10</td>
<td>459</td>
<td>22.43</td>
<td>0.79</td>
<td>617.28</td>
<td>10</td>
</tr>
<tr>
<td>15</td>
<td>952</td>
<td>22.32</td>
<td>0.65</td>
<td>770.47</td>
<td>9</td>
</tr>
<tr>
<td>20</td>
<td>1469</td>
<td>22.31</td>
<td>0.51</td>
<td>975.95</td>
<td>9</td>
</tr>
<tr>
<td>25</td>
<td>2314</td>
<td>22.28</td>
<td>0.33</td>
<td>1195.90</td>
<td>9</td>
</tr>
<tr>
<td>30</td>
<td>3602</td>
<td>22.24</td>
<td>0.28</td>
<td>1728.60</td>
<td>8</td>
</tr>
<tr>
<td>35</td>
<td>9561</td>
<td>22.01</td>
<td>0.02</td>
<td>21322.00</td>
<td>6</td>
</tr>
<tr>
<td>40</td>
<td>29600</td>
<td>22.01</td>
<td>0.02</td>
<td>21347.96</td>
<td>6</td>
</tr>
</tbody>
</table>

Table 3. The numerical results from JERS-1 image

<table>
<thead>
<tr>
<th>R</th>
<th>Iterations</th>
<th>Mean Variance</th>
<th>ENL</th>
<th>No. of Classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>244</td>
<td>22.48</td>
<td>1.21</td>
<td>416.38</td>
</tr>
<tr>
<td>10</td>
<td>459</td>
<td>22.43</td>
<td>0.79</td>
<td>617.28</td>
</tr>
<tr>
<td>15</td>
<td>952</td>
<td>22.32</td>
<td>0.65</td>
<td>770.47</td>
</tr>
<tr>
<td>20</td>
<td>1469</td>
<td>22.31</td>
<td>0.51</td>
<td>975.95</td>
</tr>
<tr>
<td>25</td>
<td>2314</td>
<td>22.28</td>
<td>0.33</td>
<td>1195.90</td>
</tr>
<tr>
<td>30</td>
<td>3602</td>
<td>22.24</td>
<td>0.28</td>
<td>1728.60</td>
</tr>
<tr>
<td>35</td>
<td>9561</td>
<td>22.01</td>
<td>0.02</td>
<td>21322.00</td>
</tr>
<tr>
<td>40</td>
<td>29600</td>
<td>22.01</td>
<td>0.02</td>
<td>21347.96</td>
</tr>
</tbody>
</table>

Table 1 shows quantitative comparisons of the homogeneity index, $U$, by Eq. (15) with $M = 5$ and the $RUMA$ of Eq. (16) to our proposed algorithm. The $L$ values of speckle noise ranging from 4 to 16 appear in the first column of Table 1. These values are used to generate the speckle noise $R_L$ in Eq. (1); therefore, synthesis SAR image $F_L$ is constructed by $R_L$ multiplying with noise free image $I$ in Fig. 2(a). The second column illustrates the noise magnitude, which consists of before and after segmentation in the form of signal to noise ratio (SNR). ENL is calculated at the rectangular position $[(1, 1), (68, 78)]$ as shown with before and after segmentation. The column of iterations is the number of repetitions of the proposed algorithm after assigning the criteria $R = 4$ for all $L$-values. The controlling of diffusion strength $K$ and the step-size of diffusion are set to 0.013 and 0.2, respectively. The Gaussian function regulates the image data with a scale $\sigma = 0.9$.

Fig. 3 shows comparison results of the proposed algorithm with the fuzzy c-Means (20) and Zaart’s method (21). In this comparison, the synthetic image (Fig. 2(a)) is contaminated with the speckle noise by varying the look numbers from 4 to 16 to assert the accuracy and homogeneity in each region. Fig. 3(a) illustrates $RUMA$ values, in which our algorithm has a misclassification rate lower than the fuzzy c-Means and Zaart’s method. Fig. 3(b) depicts the ability of the segmentation algorithms that can estimate the radar cross sections (3) or mean values of the segmented image, which are measured on the homogeneity index $U$.

4.2 Segmentation Results Several illustrations and evaluations have been done on ERS-1/AMI and JERS-1/SAR satellite data (24). These test data are selected from West-Thailand in Kanchanaburi province (coordinates 99°5’ E; 14°0’ N). The area consists of sparse forest, river, urban, and agricultural lands as shown the ground-cover (25) in Fig. 8. Figure 4(a) illustrates the ERS-1 image, which has a pixel spacing of
15 m and the image size, $256 \times 256$ pixels with 8 bits per pixel (taken on 22 November 1991). Figure 5(a) shows the JERS-1 image with a pixel spacing of 12.5 m and the image size, $256 \times 256$ pixels with 16 bits per pixel (taken on 22 September 1992).

The experimentation results, which are depicted in Fig. 4(b-d) and 5(b-d), were processed by our algorithm at a difference ratio of the homogeneous criteria, $R$. The homogeneous areas that are employed to estimate the standard deviation to mean values, are defined on the rectangular coordinates $[(142, 84), (154, 100)]$ for Fig. 4 and $[(27, 170), (57, 193)]$ for Fig. 5. These results correspond with Table 2 and 3 that show the algorithm’s
Fig. 7. Segmented results of JERS-1 processed by: (a) proposed algorithm, (b) fuzzy c-Means (20), (c) Zaart et al. (21)

parameters depending on the given value $R$.

Table 2 and 3 illustrate the numerical results of the SAR segmentation from the ERS-1 and JERS-1, respectively. In the Tables, $R$ is defined in the rough scale from 5 to 40. The $R$ criterion provides the iteration processes with a halting mechanism, when the diffusion process propagates until the noise ratio is greater than the homogeneous criteria.

Figure 6 and 7 illustrate the segmented results of ERS-1 and JERS-1, respectively. The segmented images of the proposed algorithm use $R = 40$, the iteration numbers equal 29,600 for ERS-1 and 38,235 for JERS-1. From $R = 40$, the segmented results have 6 classes for ERS-1 and JERS-1. In the comparison, we set the number of classes of fuzzy c-Means and Zaart et al. equal to our algorithm. However, the number of classes of Zaart et al. are defined by the gradient of the histogram of the input image, which depends on iterated smoothing with a median filter (21). For controlling the number of classes of Zaart et al., median filter with $3 \times 3$ size of mask was operated 5 and 8 times for ERS-1 and JERS-1, respectively. Fig. 6(a) shows the segmented image by our method, where the homogeneity index, $U$, of the segmented image is 0.965. Fig. 6(b) illustrates the segmented image of fuzzy c-Means ($U = 0.912$) and Fig. 6(c) is processed by Zaart’s algorithm ($U = 0.896$), with $L = 3.040$ at the rectangular coordinates $[(142, 84), (154, 100)]$. Fig. 7(a) shows the segmented result by our method, which has the homogeneity index of $U = 0.964$. Fig. 7(b) illustrates the segmented results by the fuzzy c-Means ($U = 0.912$) and Fig. 7(c) is segmented with algorithm of Zaart et al. ($U = 0.883$), with $L = 2.032$ at the rectangular coordinates $[(27, 170), (57, 193)]$.

5. Discussion

The results presented above must not be thought of as a comprehensive assessment of what is possible using SAR over segmentation methods. Rather, the analysis has illustrated a method for quantitatively comparing the performance of a number of approaches to segment the SAR based on a small number of images from a particular area using only the homogeneous criteria.

The proposed algorithm is a semi-automatic method that can estimate the mean of each region when a user provides the rectangular coordinate and $R$ value. As seen from Fig. 4 and 5, the difference of $R$ values provides the different segmentation results, which cor-
respond to Table 2 and 3. Both tables illustrate the columns of mean and variance that descend from the $R$ value. As seen from the first rows, they are the original images. When the images are processed with $R = 5$, the anisotropic diffusion operated at 244 iterations for ERS-1 and 508 iterations for JERS-1. The segmented results have mean, variance, and ENL at the given rectangular region equal to 22.48, 1.21, and 416.38 for ERS-1 and equal to 33.49, 3.53, and 317.73 for JERS-1, respectively. Then $R$ values, increasing the homogeneity in the process region, will be increased as seen from the ENL value that conditioned from the iteration numbers of the diffusion process. However, increasing the $R$ value does not cover all conditions. If the selected rectangular region is incapable of becoming homogeneous; then, the segmented results become to wrong classes. Thus our experimentation the water regions are selected to avoid the non-homogeneous regions and to prevent the case of misclassify.

The experimentation results in Fig. 6 and 7 were set $R = 40$ to estimate the radar cross section values of each region corresponding with resources that the images covered. Homogenous regions of the segmented image are grown by increasing $R$ value, which should be declared corresponding with a number of objects in input image. The proposed algorithm can estimate the class numbers in an image depending on the homogeneity criterion $R$, which is defined by the user underlying a homogenous region of the input data in rectangular coordinates. The higher the value of $R$ is, the lower the number of classes as seen from Fig. 4 and 5. However, the number of classes depends directly on the detail of an input image as seen from the images ERS-1 and JERS-1 where the bits per pixel are 8 and 16, respectively. JERS-1 has more class numbers than the ERS-1 as shown in Fig 6(a) and 7(a).

6. Conclusions

The segmentation of SAR images is important in the estimation and classification of agricultural land, forests and a range of different terrain types. For the segmentation algorithm, anisotropic diffusion in a logarithm domain is adapted for growing the regions without defining any seed pixels. The algorithm modifies the diffusion process by the decomposition of the diffusion tensor to improve the criterions of contour pixels and to grow the regions in optimum boundary. The superior performance of the adaptive diffusion method is in boosting up the boundary magnitude meanwhile smoothing out the speckle noise and maintaining the homogenous regions as seen from the ENL values in Table 1-3. The proposed algorithm can use the information in SAR images to adapt the parameters of anisotropic diffusion for segmentation, such as the numbers of iteration and the growing region process given by the homogeneity critereia. The effectiveness of the proposed method has been demonstrated through empirical and visual assessments, which are compared with fuzzy c-Means and Zaart’s algorithm.

Acknowledgment

The authors would like to thank Mr. Shamus T. Neary for helping with the editing process.

(Manuscript received April 1, 2007, revised Sep. 28, 2007)

References

(22) Y.J. Zhang, and H. Luo: “Optimal selection of segmentation


(24) SAR and optical sensor image: http://www.eorc.nasda.go.jp/EORC/Gallery/Southeast_Asias/Thailand/kanchana_01.html


Sathit Intajag (Non-member) received the M. Eng. and D. Eng. Degree in electrical engineering from the King Mongkut’s Institute of Technology Ladkrabang (KMITL), Thailand, in 1998 and 2005, respectively. Since 1998, he has been instructor at the Department of Industrial Instrumentation Technology of KMITL. He was Assistance Professor and Associate Professor in 2003 and 2006, respectively. His research interests include signal processing, statistical analysis, fuzzy system.

Vittaya Tipsuwanporn (Non-member) received the B. Ind. and M. Eng. Degree in electrical engineering from the King Mongkut’s Institute of Technology Ladkrabang (KMITL), Thailand, in 1985 and 1989, respectively. Since 1986, he has been instructor at the Department of Industrial Instrumentation Technology of KMITL. He was Assistance Professor and Associate Professor in 1995 and 1998, respectively. From 2000, he is a Ph.D. student at KMITL. His research interests include measurement and control system and non-linear dynamics in power electronics.

Fusak Cheevasuvit (Non-member) received the B. Eng. and M. Eng. degree in electrical engineering from the King Mongkut’s Institute of Technology Ladkrabang (KMITL), Thailand, in 1977 and 1979, respectively. He also received the Doctor of Engineering degree from the Ecole Nationale Superieure des Telecommunications (Telecom Paris), Paris, in 1984. He is an Associate Professor.