DETECTING THE TOPOGRAPHIC CHANGES OF SPATIAL FEATURES FROM SAR SATELLITE IMAGES BASED ON THE MULTILAYER LEVEL SET APPROACH

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ABSTRACT

The areas covered by a river play an important role in analyzing the causes of debris flows. The damage caused by debris flows costs over a thousand million dollars in Taiwan. Usually, after natural disasters like typhoons and earthquakes have occurred, the topographic conditions are changed. How to locate these topographic changes is an important research issue for protecting people from natural disaster-related damages. Remote sensing is an efficient way to study topographic conditions occurring before and after in areas affected by natural disasters. Synthetic aperture radar (SAR) provides a remote sensing technique for exploring the ground truth in imaged areas in day and night. The interpretations of SAR images play an important part in analyzing the characteristics of the imaged areas. However, the effects of speckle signals make the interpretation of SAR satellite images difficult. Mumford and Shah proposed dividing an image into a set of homogeneous sub-regions, such that the energy contained in the image can be minimized. Based on this minimization of the energy, the multilayer level set method implicitly presents the regional boundaries as several nested level lines. By increasing the number of iterations and preselected level values, these lines evolve close to the level boundaries based on the energy minimization. The research results demonstrate that the proposed algorithm can be used to analyze given SAR images, and that the analyzed results can provide an important clue in studying the behavior of debris flows.

INTRODUCTION

Synthetic aperture radar (SAR) provides a remote sensing technique for exploring the ground truth in imaged areas in day and night. The interpretation of SAR images plays an important part in analyzing the characteristics of the imaged areas. However, the effects of speckle signals make the interpretation of SAR satellite images difficult. Several researches have been proposed to solve this difficulty. In general, these proposed researches can be divided into two groups: one group focuses on developing filters to remove the effects of speckle signals, and the other employs a region-based approach to divide the given image into several sub-groups such that each sub-group is homogeneous. The filters developed for removing the effects of speckle signals are based on statistical theory and edge detection (Lee, 2009; Argenti, 2002; Germain, 2000). Bias and blurring problems are usually introduced in these developed filters, and post-processing procedures are needed to eliminate the problems. On the other hand, region-based approaches based on region growing are employed and lead to the same problems (Ayed, 2005). Recently, a curve evolution based on level sets has been proposed for application on optical images.

The idea of an evolving curve can be traced back to the late 1980s. The concept of an evolving curve is that an initial curve will automatically move to the regional boundaries according to the principle of minimum energy. In 1988, Kass and Witkin proposed the snake theory where extracting regional boundaries with the iteration approach is based on minimizing the energy contained in the image (Kass, 1988). The snake model is known for using parameters to represent the curves or surfaces (Cohen, 1991). Kichenassamy extracted regional boundaries with partial differential equations and evolving curves (Kichenassamy, 1995). With the algorithms mentioned above, the initial curves need to be chosen close to the objects that need to be extracted. If the initial curves are too far away, the algorithms will come with numerical instability. In order to solve the problem of numerical instability, Malladi applied the level set approach to implement the evolving curve algorithm (Malladi, 1995). The level set approach is proposed by Osher and Sethian to simulate physical phenomena using a numerical approach (Osher, 1988). Vese builds the connections between evolving curve algorithms and multiphase classification. For image classification, Mumford and Shah proposed a minimal partition of the whole image into limited sub-regions (Mumford, 1989). Chan and Vese solved the Mumford and Shah equation for implementing the level set approach by assuming that the pixel values in the sub-regions are constant (Chan, 2001).

Furthermore, Vese extended the approach for multiphase object detection with two implicit functions and four-color theory to classify the image (Vese, 2003). Several researches based on curve evolution and level sets have been successfully employed on optical images (Chan, 2001; Malladi, 1995) and thermal infrared images (Huang, 2010).

In natural disaster management, the topographic changes after natural disasters play an important role in establishing policies to prevent the changes from causing financial loss and deaths of people. In this paper, we use the multilayer level set method, based on implicit curve evolution, to automatically locate regional boundaries without manual input. Mumford and Shah indicate that segmentation can be a hindrance to image partition because the energy stored within the image can be minimized. They propose partitioning an image into a set of homogenous sub-regions (Mumford and Shah, 1989). Concurrently, Osher and Sethian proposed and developed the level set method, a numerical approximation which can automatically detect the interior contours of sub-regions (Osher and Sethian, 1988). In this paper, initial curves with implicit representations, called level set functions, are employed to automatically locate the regional boundaries. The implicit representation is defined as the isocontour of some function (Osher and Fedkiw, 2002). The initial curves stop at the regional boundaries where the energy function, as proposed by Mumford and Shah, converges. SAR images collected on March 31st, 2007 and May 5th, 2007, were used to evaluate the performance of the multilayer level set algorithm. In the organization of this paper, we introduce the multilayer level set model in section 2. The processing scheme and numerical results processed with the multilayer level set method and the optimum statistical classifiers are illustrated in section 3. Finally, we offer a discussion and some conclusions.

MULTILAYER LEVEL SET DESCRIPTION

Let $\mathbf{I}:\Psi \to \Re^n$ be a given intensity SAR image, and Ψ be an open, bounded and connected domain with a Lipschitz boundary. The segmentation process is to partition a intensity SAR image, **I**, into a set of sub-regions, $\Omega_{i\in[1,N]}$. Let $\Omega_i \subset \Psi$, $i \in [1,N]$ and $\Omega_i \cap \Omega_j = \varnothing,\ \forall i \neq j$; in a word, the image domain is composed with a set of sub-regions, $\cup_{i=1}^{N} \Omega_i = \Psi$, and each sub-region is homogeneous. For a L-look SAR image, the image is modeled as a Gamma distribution of the mean intensity c_i of sub-region Ω_i and a number L of looks as follows (Goodman, 1975):

$$\mathbf{P}_{c_i,L}(\mathbf{I}(r)) = \frac{L^L}{c_i\Gamma(L)}\left(\frac{\mathbf{I}(r)}{c_i}\right)^{L-1} e^{-\frac{L\mathbf{I}(r)}{c_i}} . \tag{1}$$

The c_i is mathematically defined as (Chung, 2009):

$$c_i = \frac{\int_{\Omega_i} I(r)dr}{\int_{\Omega_i} dr} . \tag{2}$$

Therefore, the given intensity SAR image can be modeled with maximizing the likelihood and is shown as follows (Ayed, 2005):

$$\Omega = \arg\max_{\Omega}\left(\prod_{r\in\Omega_1}\mathbf{P}_{\mathbf{c}_1,L}(\mathbf{I}(r))\prod_{r\in\Omega_2}\mathbf{P}_{\mathbf{c}_2,L}(\mathbf{I}(r))\cdots\prod_{r\in\Omega_N}\mathbf{P}_{\mathbf{c}_N,L}(\mathbf{I}(r))\right) . \tag{3}$$

After logarithmic and algebraic operations, the maximizing the likelihood can be transformed to the problem of minimizing the segmentation criterion (Ayed, 2005):

$$\mathbf{C} = \sum_{i=1}^{N}\left(\int_{\Omega_i} dr\right)\log c_i = \sum_{i=1}^{N} C_i\left(\int_{\Omega_i} dr\right) . \tag{4}$$

The minimizing segmentation criterion is an equation for recovering the optimum partition with constant c_i and sub-regions Ω_i .

Mumford and Shah proposed obtaining the optimal piecewise-constant approximation, Ω , of a given SAR image, f , and partitioning the images into a set of sub-regions such that each sub-region is homogenous (Mumford, 1989). The approximation is composed of a set of sub-regions, Ω_i , and their boundaries, $\partial\Omega_i$. Let the contours shown in the image be represented by level lines of the implicit function, . In this paper, two implicit functions, ϕ_1 and ϕ_2 , are employed. are employed. Based on the four-color theorem, a given image can be fully partitioned into sub-regions with two implicit functions (Vese, 2002). In the multilayer approach, the two implicit functions partition an image into sub-regions with distinct levels $\{l_1 < l_2 < \cdots < l_m\}$ and $\{k_1 < k_2 < \cdots < k_n\}$ for the implicit functions, ϕ_1 and ϕ_2 , respectively. The relationships between the sub-regions in the approximation and the functions, ϕ_1 and ϕ_2 , are defined as follows:

$$\Omega_{ij} = \{x \in \Omega : l_i \le \phi_1(x) \le l_{i+1}, k_j \le \phi_2(x) \le k_{j+1}\} \tag{5}$$

In order to find the solution to the problem proposed by Mumford and Shah, Chung and Vese proposed the definition of the multilayer level energy function, with constant sub-region pixel values:

$$\begin{aligned} E(c,\phi) = \sum_{i,j=0}^{m,n} \left|\log f - c_{i,j}\right|^2 \prod_i^{i+1} H((-1)^p(\phi_1 - l_i)) \prod_j^{j+1} H((-1)^q(\phi_2 - k_j))dx \\ + \mu\left[\sum_{i=1}^{m}\int_\Omega \left|\nabla H(\phi_1(x) - l_i)\right|dx + \sum_{j=1}^{n}\int_\Omega \left|\nabla H(\phi_2(x) - k_j)\right|dx\right] \end{aligned} \tag{6}$$

where p = 0 or 1, q = 0 or 1, H is the Heaviside function, $\mu > 0$ and is a weight parameter, and c_{ij} is the sub-regional constant (Chung, 2009). Though the Heaviside function has a different form, the paper employs the form proposed by Vese, and is defined as:

$$H(z)_\varepsilon = \frac{1}{2}\left[1 + \frac{2}{\pi}\tan^{-1}\left(\frac{z}{\varepsilon}\right)\right] \tag{7}$$

and

$$\delta_\varepsilon(z) = H_\varepsilon' = \frac{1}{\pi}\frac{\varepsilon}{\varepsilon^2 + z^2} \tag{8}$$

where ε is the parameter such that the function has a different zero while z is located in the interval, $[-\varepsilon, \varepsilon]$; otherwise, the function will be zero. The sub-regional constant, c_{ij} , is the constant specified in the sub-region, Ω_{ij} , such that pixel values are the constant, c_{ij} , in the sub-region, and is, in general, defined as follows

$$c_{ij} = \frac{\int_\Omega (\log f) H(\phi_1 - l_i) H(l_{i+1} - \phi_1) H(\phi_2 - k_j) H(k_{j+1} - \phi_2) dx}{\int_\Omega H(\phi_1 - l_i) H(l_{i+1} - \phi_1) H(\phi_2 - k_j) H(k_{j+1} - \phi_2) dx} \tag{9}$$

For sub-regional constants located at $\Omega_{i0}, \Omega_{in}, \ldots,$ and Ω_{mn} , the sub-regional constants have a similar form to (5) but a few modifications need to be made (details can be found in Chung's paper). The optimal piecewise-constant approximation proposed by Mumford and Shah can be shown as:

$$\begin{aligned} \Omega = & \sum_{i=1}^{m-1}\sum_{j=1}^{n-1} c_{ij} H(\phi_1 - l_i) H(l_{i+1} - \phi_1) H(\phi_2 - k_j) H(k_{j+1} - \phi_2) + \sum_{i=1}^{m-1} c_{i0} H(\phi_1 - l_i) H(l_{i+1} - \phi_1) H(k_1 - \phi_2) + \\ & \sum_{i=1}^{m-1} c_{in} H(\phi_1 - l_i) H(l_{i+1} - \phi_1) H(\phi_2 - k_n) + \sum_{j=1}^{n-1} c_{0j} H(l_1 - \phi_1) H(\phi_2 - k_j) H(k_{j+1} - \phi_2) + \\ & \sum_{j=1}^{n-1} c_{mj} H(\phi_1 - l_m) H(\phi_2 - k_j) H(k_{j+1} - \phi_2) + c_{00} H(l_1 - \phi_1) H(k_1 - \phi_2) + c_{0n} H(l_1 - \phi_1) H(\phi_2 - k_m) + \\ & c_{m0} H(\phi_1 - l_m) H(k_1 - \phi_2) + c_{mn} H(\phi_1 - l_m) H(\phi_2 - k_n) \end{aligned} \tag{10}$$

The implicit functions, ϕ_1 and ϕ_2 , are used to find the optimum piecewise-constant approximation and are numerically built via the level set method. For minimizing the defined energy shown in (6), the differential of the energy with respect to the implicit functions can be transformed as the differential of the implicit functions with respect to time. The relationship is shown as follows:

$$\frac{\partial \phi}{\partial t} = -\frac{\partial E}{\partial \phi} \tag{11}$$

Therefore, the differential results can be written as

$$\begin{aligned}
\frac{\partial \phi_1}{\partial t} = {} & \sum_{i=1}^{m-1}\sum_{j=1}^{n-1}\left|\left(\log f\right)-c_{ij}\right|^2[-\delta(\phi_1-l_i)H(l_{i+1}-\phi_1)H(k_{j+1}-\phi_2)H(\phi_2-k_j)+\delta(l_{i+1}-\phi_1)H(\phi_1-l_i)H(\phi_2-k_j)H(k_{j+1}-\phi_2)]+ \\
& \sum_{i=1}^{m-1}\left|\left(\log f\right)-c_{i0}\right|^2[-\delta(\phi_1-l_i)H(l_{i+1}-\phi_1)H(k_1-\phi_2)+\delta(l_{i+1}-\phi_1)H(\phi_1-l_i)H(k_1-\phi_2)]+ \\
& \sum_{i=1}^{m-1}\left|\left(\log f\right)-c_{in}\right|^2[-\delta(\phi_1-l_i)H(l_{i+1}-\phi_1)H(\phi_2-k_n)+\delta(l_{i+1}-\phi_1)H(\phi_1-l_i)H(\phi_2-k_n)]+ \\
& \sum_{j=1}^{n-1}\left|\left(\log f\right)-c_{0j}\right|^2\delta(l_1-\phi_1)H(\phi_2-k_j)H(k_{j+1}-\phi_2)-\sum_{j=1}^{n-1}\left|\left(\log f\right)-c_{mj}\right|^2\delta(\phi_1-l_m)H(\phi_2-k_j)H(k_{j+1}-\phi_2)+ \\
& \left|\left(\log f\right)-c_{00}\right|^2\delta(l_1-\phi_1)H(k_1-\phi_2)+\left|\left(\log f\right)-c_{0n}\right|^2\delta(l_1-\phi_1)H(\phi_2-k_n)-\left|\left(\log f\right)-c_{m0}\right|^2\delta(\phi_1-l_m)H(k_1-\phi_2)- \\
& \left|\left(\log f\right)-c_{mn}\right|^2\delta(\phi_1-l_m)H(\phi_2-k_n)+\mu\sum_{i=1}^{m}\left[\delta(\phi_1-l_i)div\left(\frac{\nabla\phi_1}{\left|\nabla\phi_1\right|}\right)\right]
\end{aligned} \tag{12}$$

$$\begin{aligned}
\frac{\partial \phi_2}{\partial t} = {} & \sum_{i=1}^{m-1}\sum_{j=1}^{n-1}\left|\left(\log f\right)-c_{ij}\right|^2[-\delta(\phi_2-k_j)H(l_{i+1}-\phi_1)H(k_{j+1}-\phi_2)H(k_{j+1}-\phi_2)+\delta(k_{j+1}-\phi_2)H(\phi_1-l_i)H(\phi_2-k_j)H(\phi_2-k_j)]+ \\
& \sum_{j=1}^{n-1}\left|\left(\log f\right)-c_{0j}\right|^2[-\delta(\phi_2-k_j)H(k_{j+1}-\phi_2)H(l_1-\phi_1)+\delta(k_{j+1}-\phi_2)H(\phi_2-k_j)H(l_1-\phi_1)]+ \\
& \sum_{j=1}^{n-1}\left|\left(\log f\right)-c_{mj}\right|^2[-\delta(\phi_2-k_j)H(k_{j+1}-\phi_2)H(\phi_1-l_m)+\delta(k_{j+1}-\phi_2)H(\phi_2-k_j)H(\phi_1-l_m)]+ \\
& \sum_{i=1}^{m-1}\left|\left(\log f\right)-c_{i0}\right|^2\delta(k_1-\phi_2)H(\phi_1-l_i)H(l_{i+1}-\phi_1)-\sum_{i=1}^{m-1}\left|\left(\log f\right)-c_{in}\right|^2\delta(\phi_2-k_n)H(\phi_1-l_i)H(l_{i+1}-\phi_1)+ \\
& \left|\left(\log f\right)-c_{00}\right|^2\delta(k_1-\phi_2)H(l_1-\phi_1)-\left|\left(\log f\right)-c_{0n}\right|^2\delta(\phi_2-k_n)H(l_1-\phi_1)+\left|\left(\log f\right)-c_{m0}\right|^2\delta(k_1-\phi_2)H(\phi_1-l_m)- \\
& \left|\left(\log f\right)-c_{mn}\right|^2\delta(\phi_2-k_n)H(\phi_1-l_m)+\mu\sum_{j=1}^{n}\left[\delta(\phi_2-k_j)div\left(\frac{\nabla\phi_2}{\left|\nabla\phi_2\right|}\right)\right]
\end{aligned} \tag{13}$$

While the energy function defined in (6) reaches convergence with increasing iterations, the two implicit functions are stopped automatically and updated. Both partial differential equations (PDEs) are solved using the finite difference method and an iterative approach. In this paper, we extend the numerical algorithm proposed by Vese such that the solutions reach numerical stability (Vese, 2002). Both PDEs can be solved numerically in a few iterations to reach the piecewise-constant approximation. Two initial implicit functions, ϕ_1^0 and ϕ_2^0, need to be established to implement the numerical algorithm. The zero level lines generated with the implicit functions lie exactly on the sub-regional boundaries. The regional constants are then calculated to solve the partial differential equations given in (12) and (13). The piecewise-constant approximation, PCA, is iterated close to the original image for the limited regions.

PROCESSING SCHEME AND NUMERICAL RESULTS

How to remove the effects of speckle signals from a given SAR image is an important research issue in the field of SAR image interpretation. The multilayer level set approach partitions the given SAR image into several regions with predefined level values such that each region is homogeneous, and the optimal piecewise-constant approximation (PCA) can provide an image which is very close to the original image without the effects of speckle signals. To implement the multilayer level set approach, several level values need to be determined first. In this paper, a K-means approach is proposed to roughly classify the whole SAR image into K regions. Then, the average values for the classified region are calculated as the level values specified for the multilayer level set approach. After this, two implicit functions, and , are built which lie on the given intensity SAR image. From (12) and (13), the implicit functions are evolved with time. In other words, the implicit functions are slowly changed with an increasing numbers of iterations. Eventually, the energy defined by (6) reaches convergence with respect to the number of iterations, and those two implicit functions will not be evolved further. This means that the whole intensity SAR image has been partitioned into several regions according to those predefined level values such that each region is homogeneous and can be approximated by the regional constant defined by (9). The whole processing scheme is illustrated in Fig. 1.

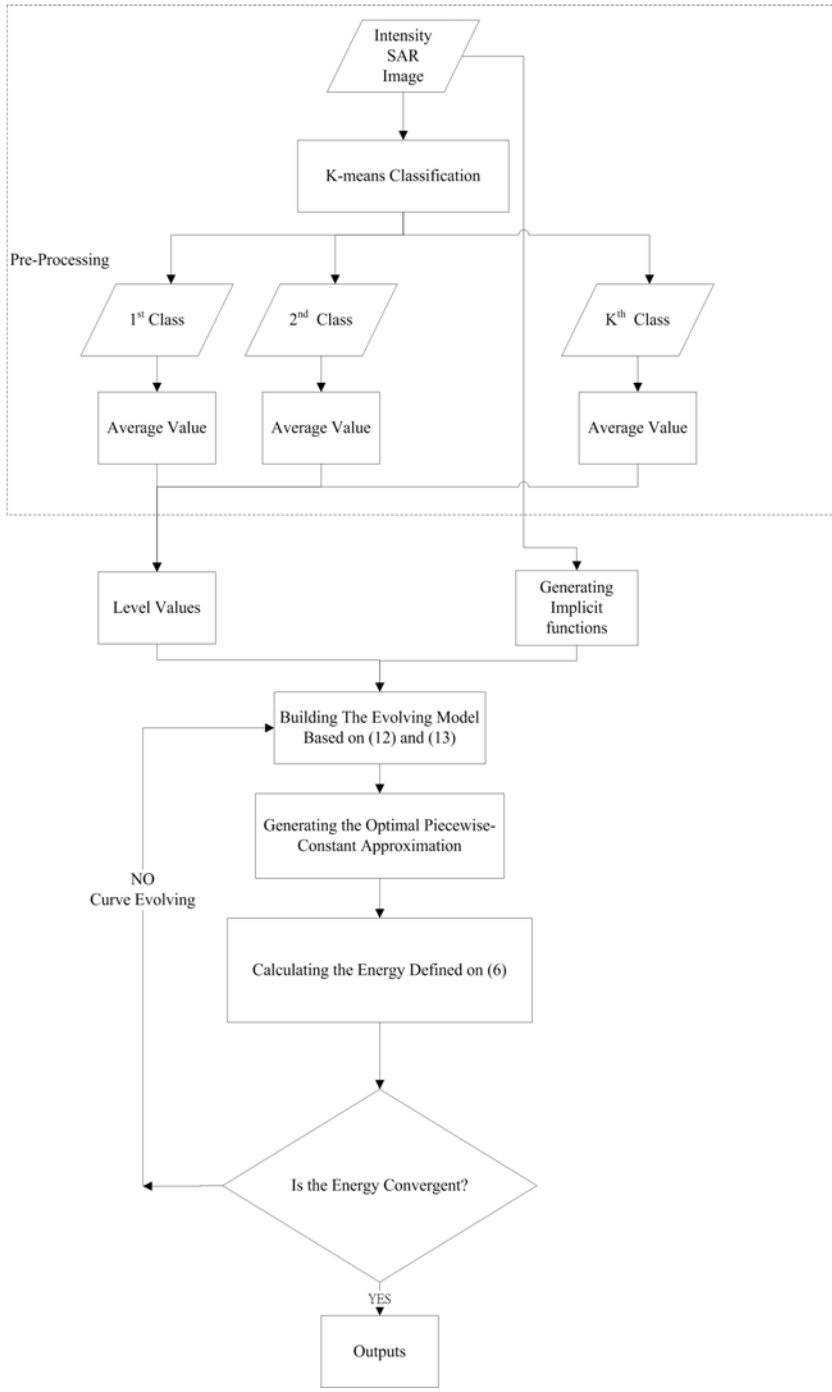

Figure 1. The processing scheme for processing an intensity SAR image by employing the multilayer level set approach.

The test SAR image was collected on March 31st, 2007, and its geographic location is located in the north of Taiwan.

Fig. 2 shows the effect of speckle signals. The effect of speckle signals usually causes difficulty in interpreting a given SAR image. Fig. 3 illustrates the results by applying the K-means approach on the given SAR image. The average values for the classified classes were calculated and used as the level values for the input of the multilayer level set approach. Fig. 4 shows two implicit functions, ϕ_1 and ϕ_2, lying on the given SAR image. Using $dt = 0.1$, $\varepsilon = 1$ and $\mu = 0.00015 \times 256 \times 256$, the processed results with respect to the number of iterations are illustrated in Fig. 5. Eventually, the original image is compared with the optimal piecewise-constant approximation in Fig. 6. In Fig. 7, we present the 3D display of the optimal piecewise-constant approximation. In Fig. 8, the relationship between the energy defined by (6) and the number of iterations is illustrated.

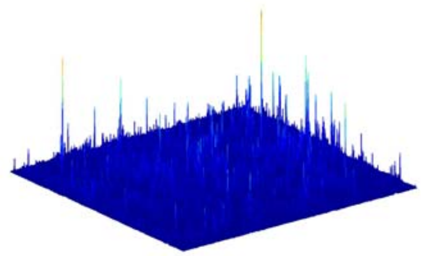

Figure 2. The effect of speckle signals shown in the given SAR image.

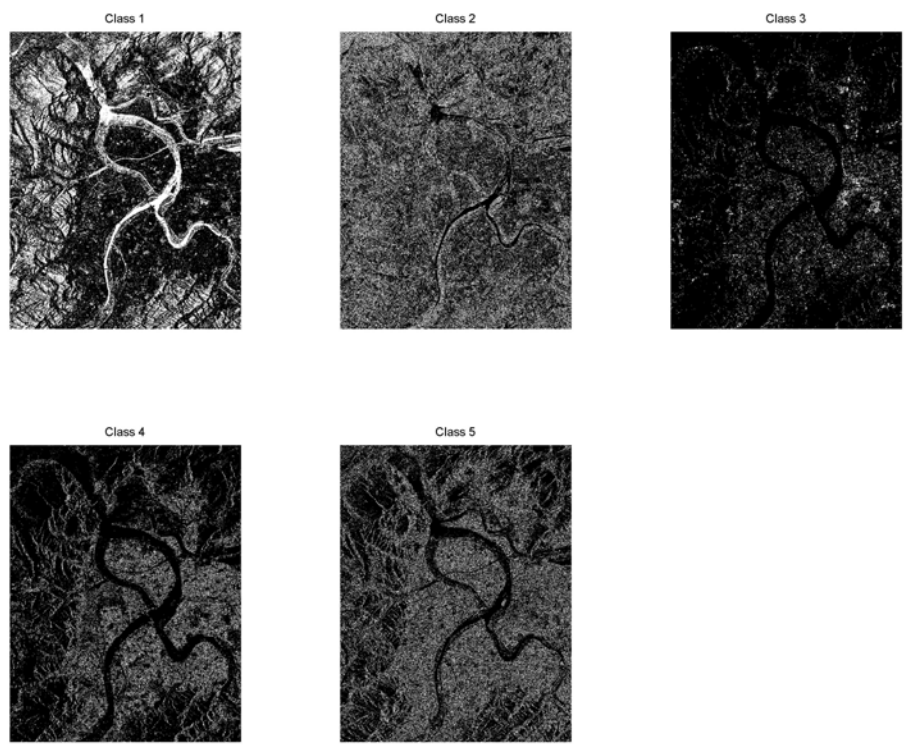

Figure 3. The classified results employing the K-means approach.

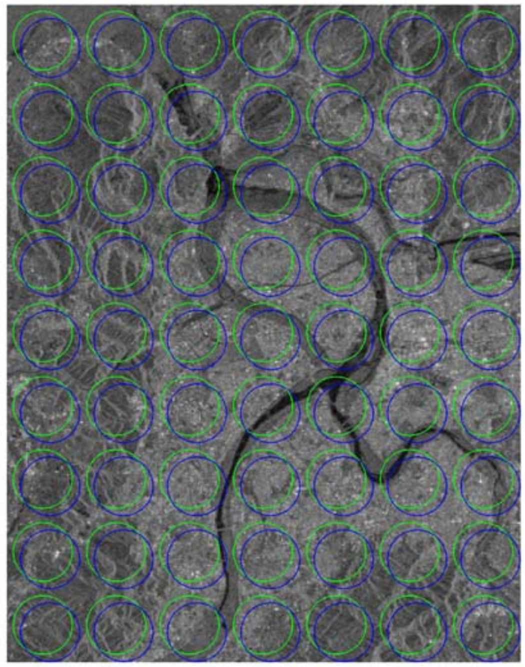

Figure 4. Two implicit functions, ϕ_1 and ϕ_2, lying on the given SAR image.

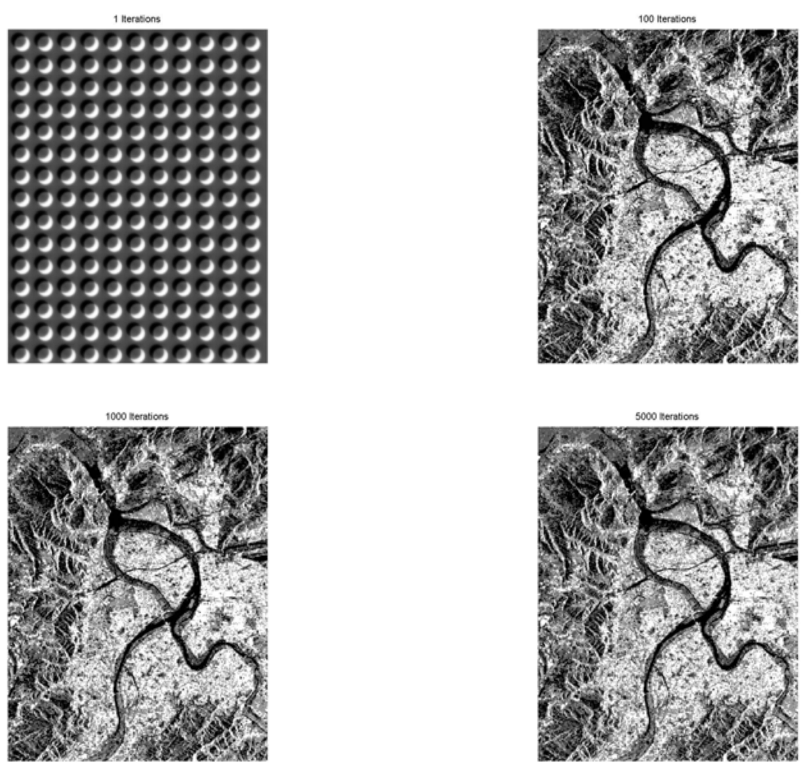

Figure 5. The generated piecewise-constant approximations.

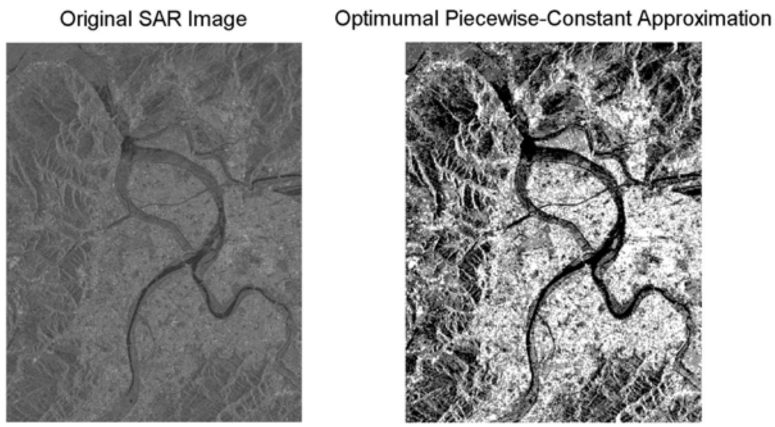

Figure 6. Visual comparison between the original image and the optimal piecewise-constant approximation.

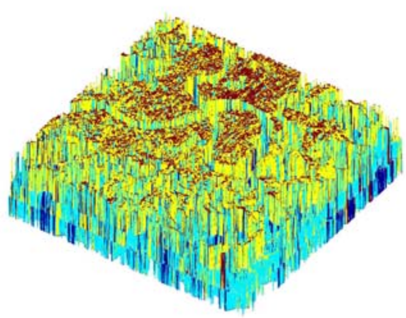

Figure 7. The 3D display for the optimal piecewise-constant approximation.

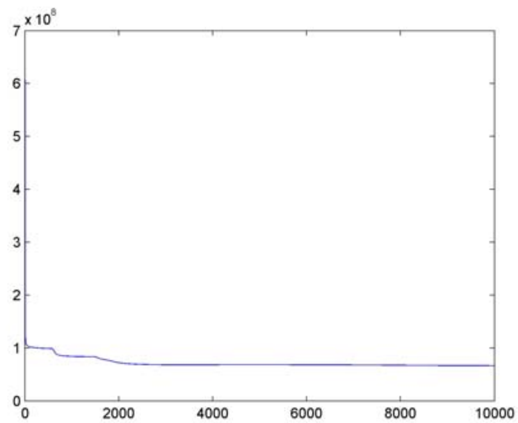

Figure 8. The relationship between the energy defined by (6) and the number of iterations.

Similarly, another SAR image collected on May 5th, 2007, was used to evaluate the performance of the multilayer level set approach. Its geographic location is located in central Taiwan. Using $dt = 0.1$, $\varepsilon = 1$ and $\mu = 0.00015 \times 256 \times 256$, t the processed results with respect to the number of iterations are illustrated in Fig. 9. In Fig. 10, the relationship between the energy defined by (6) and the number of iterations is illustrated.

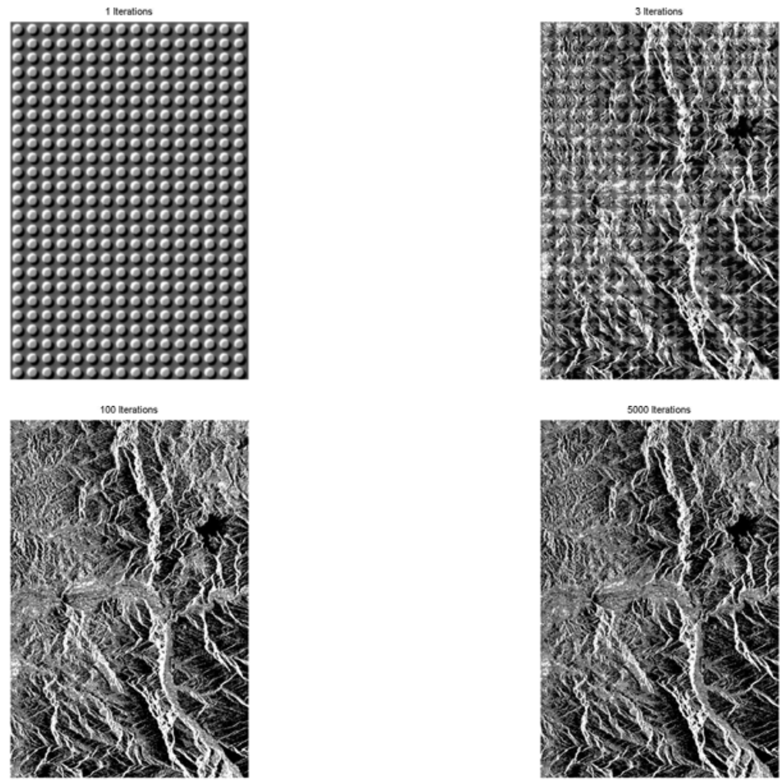

Figure 9. The generated piecewise-constant approximations.

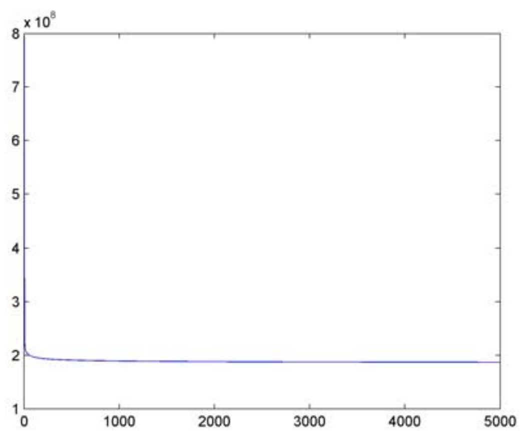

Figure 10. The relationship between the energy defined by (6) and the number of iterations.

CONCLUSIONS

The multilayer level set method is a numerically stable way to locate solutions at the global minimum. In general, several parameters need to be established before using this method. From the experimental results, the method is successful in partitioning the given SAR images into limited homogenous sub-regions. As seen in Fig. 8 and 10, the processed results can quickly reach convergence. As seen by comparing Fig. 2 and 7, the effect of the speckle signals shown in Fig. 2 are effectively reduced by employing the regional constants to replace those speckle signals. The conclusions are summarized as follows:

1. the multilayer level set approach offers a numerically stable algorithm;

2. by carefully choosing the parameters needed to implement the algorithm, the defined energy can quickly reach convergence;
3. the effect of speckle signals can be effectively reduced by employing the algorithm; and
4. the optimal piecewise-constant approximation provides a visual interpretation for the given SAR images.

These research results demonstrate that the proposed algorithm can be used to analyze given SAR images, and the analyzed results can provide important clues for studying the behavior of debris flows.

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