# SAR IMAGE TERRAIN CLASSIFICATION USING THE MODIFIED FRACTAL SIGNATURE (MFS) METHOD

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#### Abstract

The Modified Fractal Signature (MFS) method is applied to real Synthetic Aperture Radar (SAR) images containing different terrain types. Useful information for SAR image classification is obtained using this method, and the SAR image can be classified as an urban, suburban, rural, mountain or sea site. Moreover, the corresponding Fractal Area curve and Fractal Dimension curve of the image are calculated through the MFS method. The classification of different types of terrain is possible due to the fact that the terrain types encountered in SAR images, yield different values of Fractal Area curves and Fractal Dimension curves.

#### 1. INTRODUCTION

Fractals are characterised by a high degree of geometrical complexity in several groups of data as well as in images. Images, and in particular Synthetic Aperture Radar (SAR) images, can be considered as fractals for a certain range of magnifications. Moreover, fractal objects have unique properties that can be related to their geometric structure [1] – [3]. The fractal properties of images, provide interesting classification and characterization results for different terrain types encountered in real SAR images [4], [5]. For example, a SAR image of a rural area, is expected to exhibit different properties, when they are both treated as fractal objects.

In this paper the Modified Fractal Signature (MFS) method is applied to real spaceborne SAR images, provided to us by an International Working Group on SAR techniques (SET 163 Working Group). The main idea concerning this technique is the fact that different terrain types encountered in SAR images yield different characteristic values of 'Fractal Area' curves ( $A_{\delta}$ ) and 'Fractal Dimension' (or 'Fractal Signature') curves ( $F_D$ ) [5] in particular, through which classification of different types of terrain is possible.

# 2. MATHEMATICAL FORMULATION OF THE MFS METHOD

In this section the mathematical formulation of the modified Fractal Signature (MFS) method [2] - [5] is described. This 'multi – resolution' method is applied at images and it computes the values of 'Frac-

tal Area' ( $A_{\delta}$ ) and 'Fractal Dimension' (or 'Fractal Signature') ( $F_D$ ) at different scales  $\delta$  of the original image. The corresponding algorithm incorporates the so called 'blanket' technique [2] – [5] and the images are initially converted to a gray – level function g(x, y). In the 'blanket' approach all points of the three - dimensional space at distance  $\delta$  or less from the gray level function g(x, y) are considered. These points construct a 'blanket' of thickness  $2\delta$  covering the initial gray level function. The covering blanket is defined by its upper surface  $u_{\delta}(x, y)$  and its lower surface  $b_{\delta}(x, y)$ , as it is shown in Fig. 1 [5].

The upper and lower surface can be computed using an iterative algorithm ( $\delta$  iterations). Initially, the iteration number  $\delta$  equals to zero ( $\delta = 0$ ) and the gray-level function equals to the upper and lower surfaces, namely:  $u_0(x, y) = b_0(x, y) = g(x, y)$ . For iteration  $\delta = 1, 2, ...$  the blanket surfaces are calculated through the following iterative formulae:

$$u_{\delta}(x, y) = \max\{u_{\delta^{-1}}(x, y) + 1, \max_{|(m,n)-(x,y| \le 1} u_{\delta^{-1}}(m, n)\}$$

$$b_{\delta}(x, y) = \min\{b_{\delta^{-1}}(x, y) - 1, \min_{|(m,n)-(x,y| \le 1} b_{\delta^{-1}}(m, n)\}$$
(1)



Fig. 1. 'Blanket' of thickness  $2\delta$  defined by its upper  $u_{\delta}(x,y)$ and lower  $b_{\delta}(x,y)$  surface

#### CEMA'14 conference, Sofia

The image pixels (m, n) with distance less than one from pixel (x, y) are chosen in this paper as the four immediate neighbors of pixel (x, y) [3]. Equation (1) ensures that the new upper surface  $u_{\delta}$  is higher than  $u_{\delta-1}$  by at least one. Likewise, the new lower surface  $b_{\delta}$  is lower than  $b_{\delta-1}$  by at least one [3].

Subsequently, the volume of the 'blanket' is calculated from  $u_{\delta}(x, y)$  and  $b_{\delta}(x, y)$  by:

$$Vol_{\delta} = \sum_{(x,y)} (u_{\delta}(x,y) - b_{\delta}(x,y))$$
(2)

Furthermore, the 'Fractal Area' ( $A_{\delta}$ ) can be calculated as following [3]-[5] :

$$A_{\delta} = \frac{Vol_{\delta}}{2\delta} \quad \text{or} \quad A_{\delta} = \frac{Vol_{\delta} - Vol_{\delta-1}}{2} \tag{3}$$

The 'Fractal Dimension' [or 'Fractal Signature' [3]] ( $F_D$ ) can be calculated by the fractal area ( $A_{\delta}$ ) using the following formula:

$$A_{\delta} \approx \beta \delta^{2-F_D} \tag{4}$$

where  $\beta$  is a constant. In other words the 'Fractal Dimension' (*F<sub>D</sub>*) corresponds to the rate of decreasing of the 'Fractal Area' ( $A_{\delta}$ ) with increasing iteration  $\delta$ . Subsequently, from (4) it can be easily derived [4] that the 'Fractal Dimension' (*F<sub>D</sub>*) can be obtained as a slope of the function  $A_{\delta}$  in log-log scale, according to the formula:

$$F_D \approx 2 - \frac{\log_2 A_{\delta_1} - \log_2 A_{\delta_2}}{\log_2 \delta_1 - \log_2 \delta_2} \tag{5}$$

In the present application of the algorithm, we selected for convenience  $\delta_1 = 1$  and  $\delta_2 = 2, 3, 4...[3]$ -[5].

#### 3. NUMERICAL RESULTS - TRAINING DATA

In this paper, the Modified Fractal Signature (MFS) method is applied in real field spaceborne SAR images which depict different types of terrain. The images were provided to us by an International Working Group on SAR techniques, named 'SET 163 Working and are related to 4 different geographic regions in the United States of America (USA), namely in the city of New York, the city of Washington D.C., the city of Las Vegas and the state of Colorado.

From the provided real SAR images mentioned above, twenty sub- images of the same size were

extracted in order to construct the proposed terrain classifier. These twenty sub-images were organized in five groups, each one of them corresponding to the five different terrain types selected for this terrain classifier. The terrain types that are examined in this paper are the following: urban site, suburban site, rural site, mountain site and sea site. In other words, four sub-images per terrain type were selected. All twenty sub-images represent the so – called 'training data' of our proposed classifier.

The 'Fractal Area' curves ( $A_{\delta}$ ) for all twenty subimages of terrain mentioned above were calculated, and the average 'Fractal Area' curve for each type of terrain (out of 5) was calculated. The corresponding 'multiresolution' curves for these five types of terrain are shown in Fig. 2, in log – log scale (all the logarithms mentioned in this paper have as base the number two and each curve is the average of four curves). Subsequently, through the use of (5), the corresponding 'Fractal Dimension' [or 'Fractal Signature' [3]] ( $F_D$ ) curves were calculated, as shown in Fig. 3.



Fig. 2. 'Fractal Area' versus iteration  $\delta$  for each type of terrain (training data) in a log-log scale.



Fig. 3. 'Fractal Dimension' versus iteration  $\delta$  for each type of terrain (training data) in a log-log scale.

10

It appears that the value of 'Fractal Dimension' [or 'Fractal Signature'] ( $F_D$ ) contains more information about the fractal properties of each terrain type than the value of 'Fractal Area' ( $A_\delta$ ) [2] regarding the classification of different types of terrain in SAR images, and this is exactly the quantity which is used for image classification purposes [2] – [5].

The curves in Fig. 3 show a clearly different pattern (with respect to 'Fractal Dimension' values and form of the corresponding curve) for each of the five selected terrain types. These different patterns will provide to us the basis for the construction of our terrain classifier.

# 4. CLASSIFICATION RESULTS

For classification purposes, two sub-images of each terrain type [of the same size with the 'training data'] were obtained from the same SAR images. These ten sub – images construct two sets of 'testing data', namely each terrain type (urban, suburban, rural, mountain and sea site) is represented by two images, one in test data set 1 and another in test data set 2.

Each set of 'testing data' sub - images was compared to the 'training data' sub - images based on their 'distance D in the corresponding 'Fractal Dimension' curves ( $F_D$ ). Namely, for two sub - images *i* and *j* with 'Fractal Dimension' curves  $F_{Di}(\delta)$  and  $F_{Dj}(\delta)$  respectively, the 'distance D between them was computed using the following formula [2]:

$$D(i,j) = \sum_{\delta} \left[ \left( F_{Di}(\delta) - F_{Dj}(\delta) \right)^2 \cdot \log \left( \frac{\delta + \frac{1}{2}}{\delta - \frac{1}{2}} \right) \right] (6)$$

where  $\delta$  represents the number of iteration.

The above formula was applied to all possible pairs of sub images between the 'training data', Fig. 3, and the newly selected 'testing data'. The calculated 'distances D for all possible pairs are shown in Table 1. A terrain type is identified by choosing the smallest 'distance D from the corresponding 'training data'.

From Table 1 we conclude that the same terrain types between 'training' and 'test' data (for each test set) exhibit the smallest 'distance D' in 'Fractal Dimension' curves ( $F_D$ ), thus providing correct classification results in the classification experiment performed here. In other words, minimum value of

'distance D were found between the same terrain types among the training and test sub-images in the 'classification matrix' of Table 1.

Table 1. Classification Matrix

Training data	Test data 1				
	Urban	Sub- urban	Rural	Mountain	Sea
Urban	0,0254	0,0623	0,3765	1,0909	2,2352
Sub- urban	0,0316	0,0075	0,4034	1,2081	2,2353
Rural	0,4674	0,6774	0,0334	0,1092	0,501
Mountain	0,8321	1,1013	0,1915	0,0221	0,4432
Sea	1,8113	2,2272	0,8342	0,2046	0,0291
Training data	Test data 2				
	Urban	Sub- urban	Rural	Mountain	Sea
Urban	0,0077	0,0273	0,6846	1,1483	2,8118
Sub- urban	0,1038	0,0449	0,718	1,2535	2,839
Rural	0,4227	0,3634	0,0378	0,1194	0,8183
Mountain	0,793	0,6953	0,0531	0,0263	0,6564
Sea	1,7218	1,6739	0,4451	0,1818	0,0004

## 5. CONCLUSION

In this paper a novel approach for the classification of different terrain types which appear in SAR radar images is described. This classification scheme is based on the calculation of 'Fractal Dimension' 'multi – resolution' curves ( $F_D$ ) for corresponding sub – images, and comparison of 'training' and 'testing' data sets through calculation of the corresponding 'distance D' between them. Correct classification results were obtained for the classification experiment performed in this paper, based on real – life spaceborne SAR radar images.

As a future research in this area, more terrain data based on SAR radar images could be obtained for both 'training' and 'test' datasets, in order to build a more robust and more reliable terrain type classifier.

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#### CEMA'14 conference, Sofia

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