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Automated Classification of SAR Images Using Moment

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Abstract

Moment of images provides efficient descriptors and has been used in different image analysis application. The main advantage is their ability to provide invariant characteristic.
In this paper a novel methodology has been carried out to classify SAR images using the Moments. This paper also provides the overview of most commonly used of moments and then present a moment based approached for classification of SAR images. A comparison has been carried out with histogram based classification on same images for measuring the accuracy.
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Keywords: *Moments; complex moments; raw moment; classification.*

1. Introduction

An image moment is a certain particular weighted average (moment) of the image pixels' intensities, or a function of such moments, usually chosen to have some attractive property or interpretation. An analyst attempts to classify features in an SAR image by using the elements of visual interpretation to identify homogeneous groups of pixels that represents various features or land cover classes of interest. Environmental monitoring, earth-resource mapping, and military systems necessitate broad-area imaging at high resolutions. Synthetic Aperture Radar (SAR) grants such a capability. SAR systems take advantage of the long-range propagation characteristics of radar signals and the complex information processing capability of modern digital electronics to provide high resolution imagery.
Moments based features descriptors have involved into a powerful tool for image analysis application.
In image processing, computer vision and related fields, an image moment is a certain particular weighted average (moment) of the image pixels' intensities, or a function of such moments, usually chosen to have some attractive property or interpretation.
For a 2-D continuous function *f*(h,k), the raw moment of (i + j)th order is defined as the second order moments of the pixels, calculated as:

$$\mathrm{M}_{\mathrm{ij}} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} h^i k^j f(h,k)\,dhdk -----(1)$$

for h,*k* = 0,1,2,...

Adapting this to scalar (grayscale) image with pixel intensities f(h,k), raw image moments M_{ij} is given by

$$M_{ij} = \sum_{h=0}^{M}\sum_{k=0}^{N} h^i k^j f(H,k) -----(2)$$

In some cases, equation (2) may be rewritten, by considering the image as a probability density function, *i.e.*, dividing by the term (3)

$$\sum_{h=0}^{M}\sum_{k=0}^{N} f(H,k) -----(3)$$

A uniqueness theorem states that if *f*(h,k) is piecewise continuous and has nonzero values only in a finite part of the *xy* plane, moments of all orders exist, and the moment sequence (M_{ij}) is uniquely determined by *f*(h,k). Conversely, (M_{ij}) uniquely determines *f*(h,k). In practice, the image is summarized with functions of a few lower order moments.

Image moments are useful to describe objects after segmentation. Simple properties of the image which are found *via* image moments include area (or total intensity), its centroid, and information content about its orientation. .

In this work, we present a novel algorithm using moments for classification of SAR images. The necessary mathematical analysis has been carried out for this purpose. Also an attempt has been made to compare the result with histogram based classification on same images for measuring the performance of developed algorithm.
The notation of complex moments has been introduced in this paper to derive out a set of invariant features. The two dimensional Complex Moment of (i.j)th order for a image function f(h,k) , defined by :

$$C_{hk} = \int_{a1}^{a2}\int_{b1}^{b2}(x+jy)^{h}(x-jy)^{k} f(h,k)dhdk --(4)$$

Where C_{hk} are the Complex moment, h and k are nonnegative integers and j=√-1.

Section II describes the proposed methodology. Section III suggests the novel algorithm, developed in this work. Section IV describes the result and discussion. Section V gives the conclusions.

2. Proposed Methodology

Since the abrupt changes in intensity pixel value indicates class, its detection in binary or segmented image is quite straightforward. However, the classes of SAR images having minimum variations in nature.

In our methodology first we have convolute the image with a five order mask according to the X and Y direction respectively to obtain the first order moments of each points. Then the gradient is obtained by the following relation:

$\Delta f(x,y) = [\, G_X \;\; G_Y \,] = [\, \Delta f/\Delta x \;\; \Delta f/\Delta y \,]$ ……(5)

The weight of the vector is calculated as -:

$\Delta f(x,y) = \mathrm{mag}(\Delta f(x,y)) = \sqrt{(G^2{}_X + G^2{}_Y)}$ …….(6)

First order moments of points give the maximum location at the center of the original signal thus removing the noises from SAR images. For a 2-D continuous function *f*(h,k) the raw moment of order (i + j) is defined as the second order moments of the pixels is calculated as:

$$M_{ij} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} h^i k^j f(h,k)dhdk -----(7)$$

Image classification based on Third order Moments is a greedy technique because it classifies pixels into two categories.

Category1: Pixels whose values fall below the Third order Moments.

category2: Pixels whose values are equal or exceed the Third order Moments.

If M_3 is a Third order Moments value, then any pixel (i, j) for which $f(j; j) \geq M_3$ is called a class point.

For Third order Moments we compute the local intensity variations using local moment as:

1. First the overall first order moments value of the SAR image is calculated. So the pixels having lower class strength than this moment value are already discarded.

$$M_{ij} = \int_{r1}^{r2}\int_{c1}^{c2}(h-\bar{h})^{i}(k-\bar{k})^{j} f(h,k)dhdk --(8)$$

Where

$$\bar{h} = \frac{M_{10}}{M_{00}} \text{ and } \bar{k} = \frac{M_{01}}{M_{00}}$$

are the components of the centroid. M ij is the local moment and r1, r2, and c1, c2 are the row and columns. Hence the First order moment is given by

$$M1 = \int_{r1}^{r2}\int_{c2}^{c2} f((h+M_{ij})(k+M_{ij})dhdk ---(9)$$

2. Then a 3 X 3 window is splits over the SAR image and the Second order Moment of the SAR image within this window, calculated as-

$$\delta^2 = \frac{1}{9}\left(\int_{r1}^{r2}\int_{c1}^{c2} f((h+r1)(k+c1))dhdk\right) - M_{ij} --(10)$$

Now considering the sum of this First and Second order moments, the Third order Moments of that pixel is calculated Now if the gradient of this image exceeds this Third order Moments then the pixel is treated as a class. Hence the Third order Moment is calculated by the following relation

$M3 = M1 + \delta$. ……………………………(11)

In this way, the Third order Moments is generated dynamically and region wise for each pixels so that the possibility of data loss or noise is quite reduced.

If the pixel value is greater than or equal to this Third order Moment then only the pixel is treated as one class otherwise it is discarded.

3. Proposed Algorithm

- Input: SAR Images of variable size.
- Output: Classified SAR image using Moments.

1) Start.
2) Taken a SAR images.
3) Consider a 3X3 window.
4) Calculate the first order and second moments of That SAR Images.
5) Store the color feature as the complex moments is calculated of SAR image.
6) Classification SAR image using third order moments.
7) Stop.

4. Experiment Result and Discussion

In this work, synthetic aperture radar images (SAR) are considered and classified using the Third order Moment.

The figure (Fig 1 to Fig 2) shows the original SAR images and corresponding histogram. The figure (Fig 1(a) and Fig 2(a)) shows the Comparison of Original SAR image and its classified version using moments. Next the figure (Fig 1(b) and Fig 2(b)) shows the histograms of moment based classified SAR images.

Result 2:

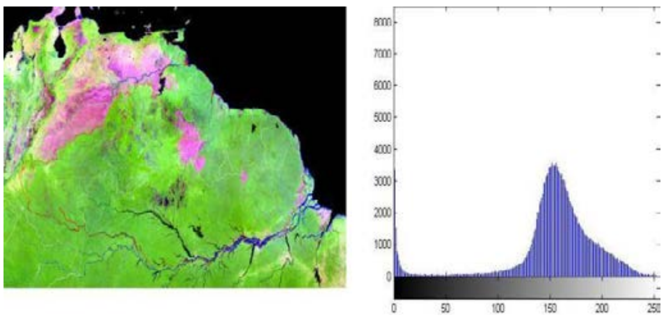

Fig2: SAR image and Histogram

After using our methodology we get the Histogram given below:

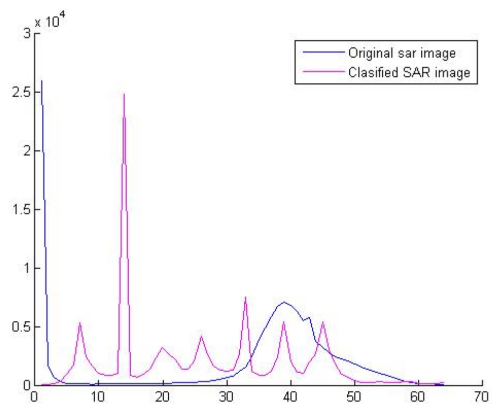

Fig2a: Comparison of Original image and Classified SAR image using moments.

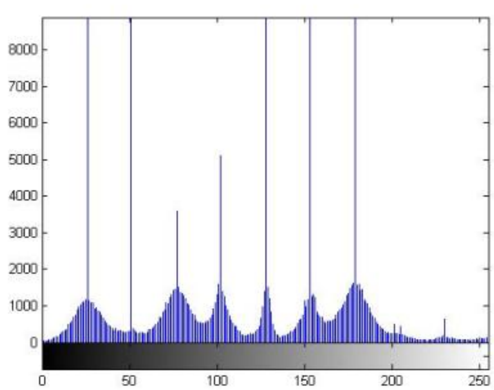

Fig2b: Histogram based classification

Result 1:

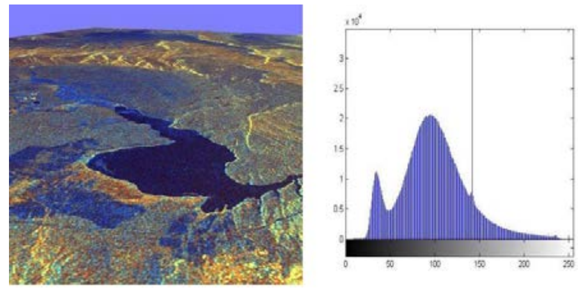

Fig1: SAR image and Histogram

After using our methodology we get the Histogram given below:

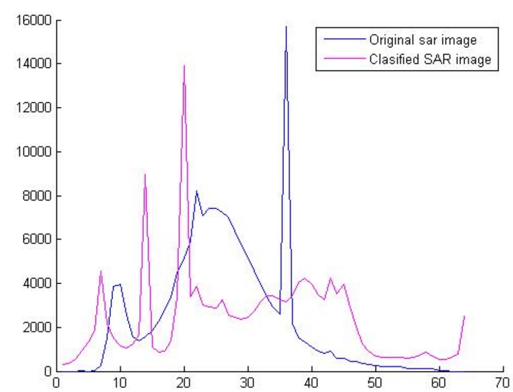

Fig1a: Comparison of Original image and Classified SAR image using moments.

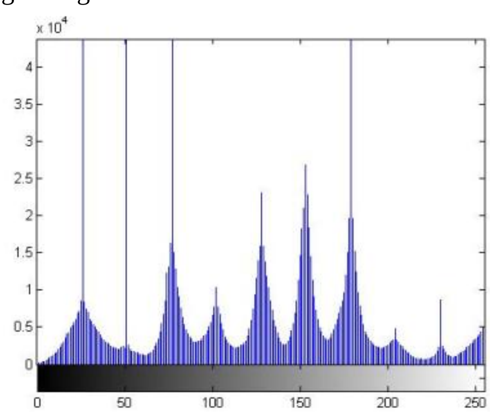

Fig1b: Histogram based classification

From result 1: considering the pick values the number of class are estimated as four (4) and considering the pick values the number of class are estimated as nine (9).
From result 2: considering the pick values the number of class are estimated as three (3) and considering the pick values the number of class are estimated as eight (8)

5. Conclusions

In this paper, a novel algorithm based on the moments for classification of SAR images is proposed. This technique is based on considering a 3X3 window and calculates successively the corresponding First, Second and Third order moments of the SAR Images and then store the color feature using Complex Moment of same SAR image for better result. The proposed algorithm gives better result compared with Histogram based classification of SAR images. Further the author will explore the possibility of using other moment functions as an extension of the result in this work.

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