Image Segmentation for rock fractures based on ARMA model

N.Natarajan*, P.Seetal, and G.Suresh Kumar*

*Civil Engineering Department, Indian Institute of Technology , Madras, Chennai, 600036.
Electrical Engineering Department, Indian Institute of Technology , Madras, Chennai, 600036

Phone: +91 (044) 2257-4292; itsrajan2002@yahoo.co.in;ee09d017@smail.iitm.ac.in;gskumar@iitm.ac.in

Abstract— Rock fracture mapping is very important in many applications related to rock mechanics. The toughest task is the extraction of the fractures from the images of the rocks. Time series model has been used in this paper for segmentation of fractures from the rock images. The model is compared with orthodox edge detection algorithms. A first order autoregressive image model has been implemented. The model has been applied for both rough as well as smooth fractures. The model was observed to perform well specifically for the rough fractures as it is sensitive to the texture of the image.

Index Terms— **Image segmentation, ARMA, rock fracture.**

I. Introduction

Rock fractures play a major role in many practical applications like water supply, geothermal energy production, and nuclear waste disposal. A comprehensive understanding of fluid flow and contaminant transport is mandatory for solving the waste disposal problems and making arrangements for adequate water and energy supply to meet the demands of the growing population. A preliminary step towards this goal is characterization of the rock fractures. Image processing proves to be an advantageous tool as it has been widely used in the past for measurement of crack widths because of their ability to extract cracks exactly. Several algorithms have been proposed by researchers for fracture detection, tracing and extraction. Wang [1] has developed a robust algorithm using edge detection and fracture tracing in order to detect the rock fractures automatically, and multi-scale technology has been adopted to alleviate the production of noise fractures. Zhao and Wang [2] have used a combination of corner segment algorithm and best rectangle fit method for measuring the width of the rock fracture aperture. Miyamoto et al. [3] have used image processing technique to recognize the crack pattern and automatic measuring method of the maximum crack width on concrete surfaces. The same study used image processing algorithm which exploits the brightness difference between the background and the cracked regions. Wang et al. [4] have presented a new methodology for rock fracture detection, description and classification based on image processing technique and support vector machine (SVM). Ho and Chen [5] have used the ARMA model, a statistical approach for extracting the water bodies and vegetation from remote sensing images. They have adopted a first order and second order ARMA model and this is different from the typical supervised classification method which requires a large number of training samples. In this paper, the first order model has been modified and implemented for rock fracture extraction. Expectation operator has been omitted in the calculation of MSE and it has been observed that similar results are obtained as in [5]. This saves several orders of computation time which is one of the major contributions of the present work.

II. FIRST-ORDER ARMA MODEL

The gray level of every pixel of the image is expressed by the equation:

$$x(i,j)=A+B*[x(i-1,j)+x(i,j-1)]+n(i,j)$$

$$\hat{x}(i,j)=A+B*[x(i-1,j)+x(i,j-1)]$$

Where n(i,j) is treated as a Gaussian white noise random praocess, $\hat{x}$ (i,j) be an estimate of x(i,j), i indicates the row index and j indicates the column index. The criterion used to minimize the mean squared error (MSE) in [5] is

$$MSE=\sum_i \sum_j E\{[x(i,j)-\hat{x}(i,j)]**2\} \tag{1}$$

In the present work, MSE is computed with only one realization as given below.

$$MSE=\sum_i \sum_j \{[x(i,j)-\hat{x}(i,j)]**2\} \tag{2}$$

saving computational effort. The approximation usually performed in time series analysis is to take the sample mean as the best estimate of the global mean given only one realization. The same procedure, although not formally proven

is experimented with the calculation of MSE, to reduce the computational burden involved with the expectation operator.
For ordinary linear regression calculation, the following optimal least squares estimator of First order ARMA parameters are obtained.

$$z(i,j) = x(i-1,j)+x(i,j-1) \tag{3}$$

$$\hat{b} = \frac{\Sigma\Sigma z(i,j)*x(i,j) - m*n*E(z(i,j))*E(x(i,j))}{\Sigma\Sigma z(i,j)*z(i,j) - m*n*E(z(i,j))*E(z(i,j))} \tag{4}$$

Where *m x n* is the size of the image matrix.

$$\hat{a} = E(x(i,j)) - \hat{b} * E(z(i,j)) \tag{5}$$

Here E(x) denotes the expectation value. This has been computed for 100 realizations obtained by adding 100 independent Gaussian white noise sequences to the original image.

In [5], threshold used is

$$Th_1 = \sqrt{\frac{2}{\pi}} + \sqrt{1 - \frac{2}{\pi}}$$

Although this threshold is considered optimal based on statistical hypotheses, it has been observed that it is not the same in the case of images containing rock with rough textures. Simulations were run for values of Th ranging from 0 to Th_1.This analysis is valid for the reason that we can expect the MSE used in the present work to be higher than the MSE used in [5]. Since the threshold for e(i.j) is computed as product of Th and MSE, it is expected that Th value which can give the same result as in [5] lies in between 0 and Th_1.Th value of 0.375 was adopted since it provides a promising result in comparison with [5]. Changing Th value from 0 to Th_1 and recomputing the whole result does not add extra computational overhead to the algorithm since this step is done only once for obtaining the Th value meant to be utilized in the algorithm. In other words this step is not part of the algorithm itself. The same Th value is applicable for all images which are summarized in the appendix.

III. Results and Discussion

The algorithm was applied on rocks with rough as well as smooth textures. The results have been shown in the Appendix. It is observed from the figures that the algorithm performs best, when compared to other existing methods to the best of our knowledge, for rocks with rough textures (Figures 2 and 3). For rocks with relatively smoother textures, although the algorithm does not perform so well as the method adopted in [5], its performance is comparable to classical operators like Sobel and Prewitt (Figures 1 and 5). The efficiency of the algorithm was further validated by its application on some general images. The algorithm has proved to be efficient. It is observed in figure 6 that the camera, which is of rough texture has been well detected by the proposed method while the smooth textured objects like the Cameraman's shirt has been well detected by [5]. This is a verification of the fact the algorithm performs well for rocks with rough texture. The appendix includes the following figures.

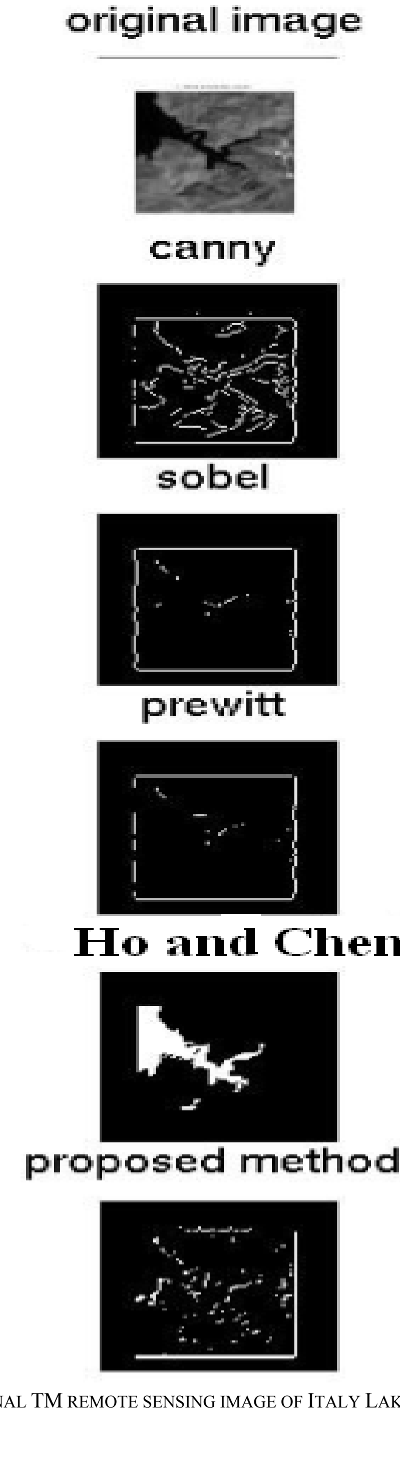

Fig. 1. Original TM remote sensing image of Italy Lake Mulagias

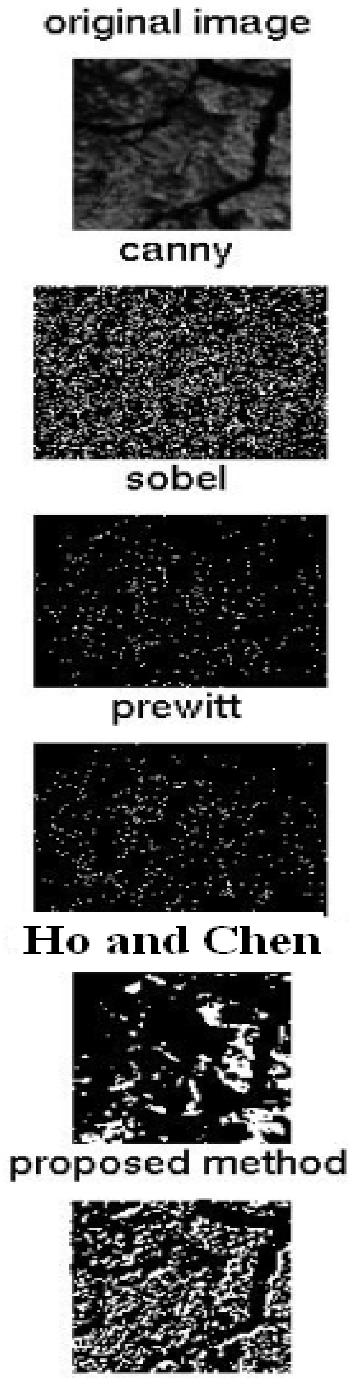

Fig. 2. Rock with rough texture I

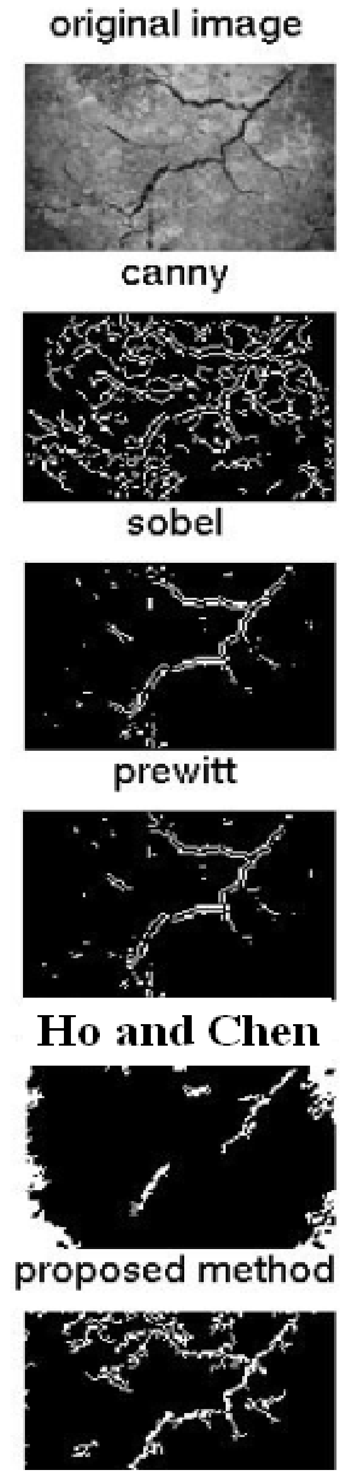

Fig. 3. ROCK WITH ROUGH TEXTURE II

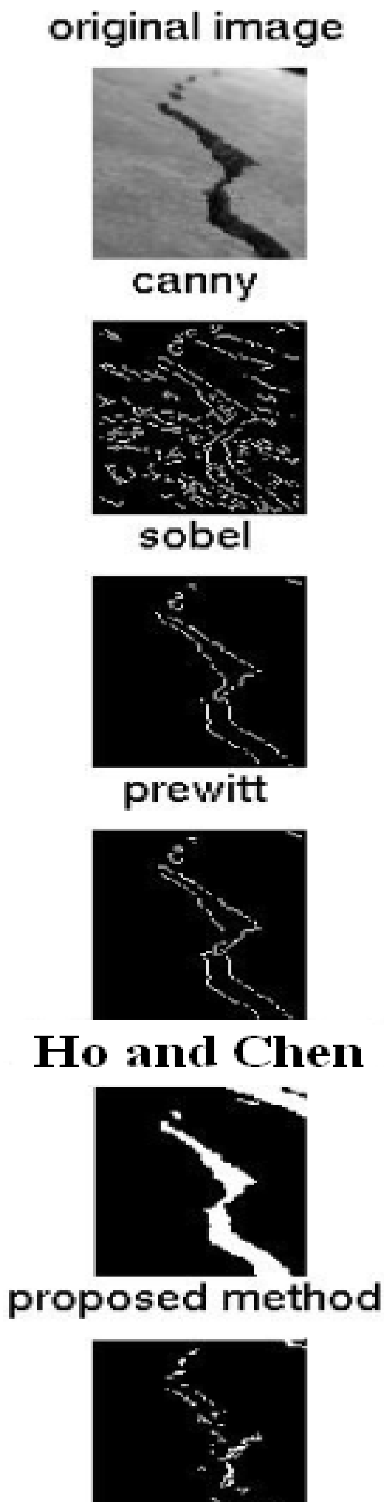

Fig. 4. ROCK WITH SMOOTH TEXTURE

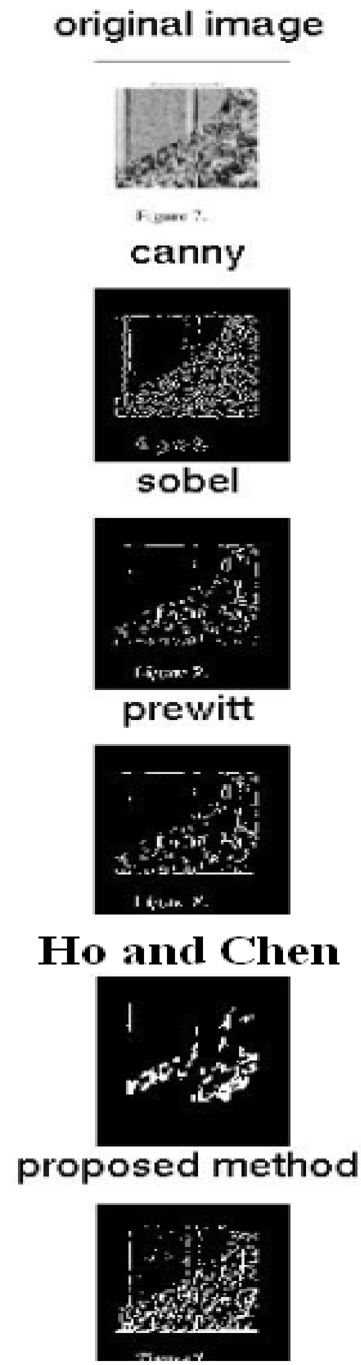

Fig. 5. ORIGINAL USC BRICK AND GRASS TWO CLASSES NATURAL SCENE

FIG. 6. CAMERAMAN

IV. REFERENCES

[1]. W. Wang, "An edge based segmentation algorithm for rock fracture tracing," *Proceedings of the Computer Graphics, Imaging and vision: New trends,* 2005.

[2]. F.Zhao and W.Wang, "Rock fracture aperture characterization based on corner segment algorithm in image analysis," *IEEE,* 2006, pp.1004-1007.

[3]. A.Miyamoto,M.A.Konno,E.Bruhwiler, "Automatic crack recognition system from concrete structures using image processing approach," *Asian journal of InformationTechnology,*Vol.6,no.5, 2007,pp. 553-561.

[4]. W.Wang, H.Liao and Y.Huang, "Rock fracture tracing based on image processing and SVM," *Third International conference on Natural Computation*, 2007.

[5]. P.G.P.Ho and C.H.Chen, "Time Series Model Based Region Growing Method for Image Segmentation in Remote Sensing Images," *IEEE*, 2004.