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A Novel Edge Detection Algorithm based on Cumulative Residual Entropy

M. A. Al-Shabi

Department of Management Information System, College of Business Administration, Taibah University, Saudi Arabia

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Abstract: In this paper, We proposed a novel edge detection algorithm based on Cumulative Residual Entropy (CRE). It is an essential concept in information theory. However, in our knowledge, it has relatively little consideration in image processing. Image thresholding and edge detection techniques play a crucial role in several of the tasks needed for pattern recognition and computer vision. In this paper, we have studied, implemented,and applied the CRE measure for edge detection. Firstly, We have defined a thresholding criterion based on the CRE measure that is related to the image. Secondly, the optimal solution is used to find edge detection image. The efficiency of the proposed approach proved by using examples from a different type of images. We have compared the proposed technique with several classic edge techniques on the same data set. The performance of the proposed method based on peak signal to noise ratio (PSNR) has been presented.

Keywords: Edge delectation, Image thresholding, Histogram, Cumulative residual entropy, Information theory.

1 Introduction

Edge detection is a vital domain in the image process. Edges characterize object boundaries that are so helpful for registration, segmentation and identification of objects during a scene. The active detection edge reduces an oversized quantity of information, however, it retains most of the critical feature of the image. Edge detection refers to the sharp discontinuities localization method in an image. These discontinuities are from different characteristics of the scene. First off discontinuities in-depth. Secondly, there are discontinuities in surface orientation, and changes within the material properties, Finally, there would be changes in scene illumination. However, the classical edge detection algorithms have principally supported the derivative by product close to the pixel of the image. Such algorithms are only elementary and convenient.They are only applicable to restricted kinds of images and are sensitive to noise, that makes it simple to cause edge rupture After decades of analysis, varied strategies of edge detection have been projected. The edge detection precision continues to be not high, that's because of the quality and variety of image content and therefore the image mechanism of digital imaging and alternative reasons. Moreover digital image is low within the ability of various kinds of images, Image detection ends up in some areas that don't seem to be ideal. Normally, most likely isn't finding an excellent edge detection algorithmic rule that may apply with success to any or all styles of images, so trying a replacement technique ought to be taken into account [1, 2] .

Shannon [3] introduced a measure of uncertainty of statistical variables, which are known as the Shannon entropy. Different entropy image measurements can defined during the construction of a statistical model for the imaging process. Recently, thresholding techniques-based entropy and its related information have been more attractive [4–16]. Several techniques and algorithms are inbuilt the entropy of image and extensively employed in image processing, precisely, medical imaging processing. The definition of entropy is to use uncertainty as a measure to explain the information contained in the data [15]. Entropy-based thresholding assumes that there are two probability distributions. Distribution is for the object class, and another is for the background. If the total of the entropies of the two classes is highest, the segmentation of the image is carried out. Sezgin and Sankur [17] mentioned that the thresholding strategies classified in six groups are in line with the

* Corresponding author e-mail: mshaby@taibahu.edu.sa

theory of the information exploit. One in all these classes uses entropy and its connected information as optimum criteria. Generally, these strategies are divided into optimal criteria-based entropy, optimal measures based cross-entropy and optimal criteria-based fuzzy entropy. The maximum entropy for image thresholding technique has been discussed by Pun [18] [19]. Kapur et al. [20] presented an improved entropy-based method for Pun criterion. Abutaleb [21] proposed a criterion, which is based on the 2D entropy that is similar to Pun's method. Brink's method [22] developed an entropy criterion based on autocorrelation functions of the threshold histograms. Li and Lee [23] proposed entropy criterion based on relative cross-entropy. By using an information-theoretic approach, Kitlerl and Illingworth [24] developed a thresholding method that minimizes the segmentation errors. Cheng et al. [25] suggested a threshold criterion based on fuzzy entropy. Rao et al. define [26] CRE as a new and robust measure of information and obtained several properties of the CRE information and discussed some of its applications in image alignment and reliability.

This measure supported the accumulative distribution function instead of the density function. CRE has some of the basic properties of entropy, overcoming some of the limitations of entropy. In this study, we propose a new algorithm to the edge detection of the proposed technique based on the CRE information measure. The performance of the proposed criterion is verified by examining it on NDT and different types of images. It has been shown through experiments that the objects are extracted successfully, then the edges are detected. The rest of the paper is organized as follows: In Section 2, cumulative residual entropy thresholding and edge detection technique based on CRE is presented. The Performance measures are presented in Section 3., Experimental results and discussion are showed in section 4 and the conclusions are presented in Section 5.

2 Cumulative residual entropy thresholding

Let I denote a gray-scale image with L gray levels.$[1,2,\ldots,L-1]$. And let for each gray level the number of pixels be given by . Therefore the total number of pixels is denoted by $M = M_0, M_1, M_2, \ldots, M_{L-1}$ Then each grey level has the probability mass function of gray level as the following:

$$f_i = \frac{m_i}{M}, f_i >= 0, \sum_{i=0}^{L-1} f_i = 1 \tag{1}$$

Suppose that the pixels within the image are divided into 2 categories A, and B. by a gray level cutoff t. The set of pixels with levels represent probability , and the set of pixels with levels$[t+1, t+2, \ldots, l-0]$ belongs to B and typically corresponds to the object and the background, or the other way around. Then the mass probability functions of the two classes are given by the following.

$$f_A = \frac{f_1}{w_1}, \frac{f_2}{w_1}, \ldots, \frac{f_t}{w_1} \tag{2}$$

$$f_B = \frac{f_{t+1}}{w_2}, \frac{f_{t+2}}{w_2}, \ldots, \frac{f_{l-1}}{w_2} \tag{3}$$

where

$$w_1(t) = \sum_{i=0}^{t} f_i, w_2(t) = 1 - w_1(t) \tag{4}$$

The prior CRE for each class is defined as:

$$CRE \quad A^{(t)} = \sum_{i=1}^{t} \frac{(1-f_i)}{w_i} \log \frac{(1-f_i)}{w_i} \tag{5}$$

$$CRE \quad B^{(t)} = \sum_{i=1}^{L} \frac{(1-f_i)}{w_2} \log \frac{(1-f_i)}{w_2} \tag{6}$$

where F_i is the cumulative distribution function of i^{th} pixel.

The CRE depends parametrically on threshold t for class A and class B .

Therefore, the CRE measure within the two classes is defined as.

$$CRE \quad (t) = w_1 CRE \quad A^{(t)} + (1-w_i) CRE \quad B^{(t)} \tag{7}$$

We maximize the $CRE \quad (t)$ inside the two classes. Once it is maximized, the brightness level t is taken into account to be the threshold. This criterion may be achieve with a small computational effort.

$$t_{(opt)} = \operatorname{argmax}[w_1 CRE \quad A^{(t)} + (1-w_i) CRE \quad B^{(t)}] \tag{8}$$

2.1 Thresholding Algorithm

The proposed algorithm defines an objective function based on CRE corresponding to two threshold classes. The threshold value is determined by maximizing the objective function.

The algorithm is described as:

1. Input Max=0, output= the maximum of CRE criterion. This is the threshold value.
2. For t =*1* to L. L is maximum of gray levels.
3. Compute the $CRE(t)$ function that corresponds to the gray level t

If $CRE(t) <$ Max, assign $CRE(t)$,to Max and, Thopt = t. End. Finally the threshold= Thopt.

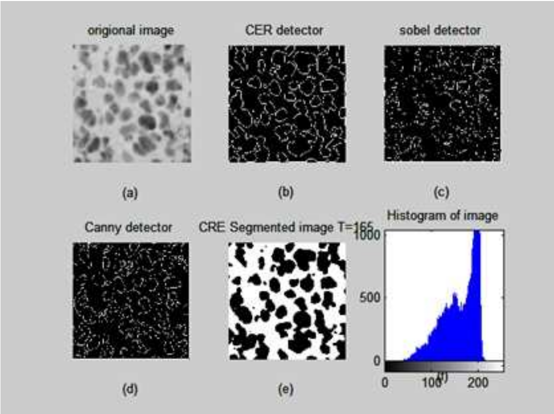

Fig1-a: (a) original, (b) CRE (proposed method), (c) Sobel, (d) Canny, (e) CRE Segmented Image (T =165), (f) Histogram

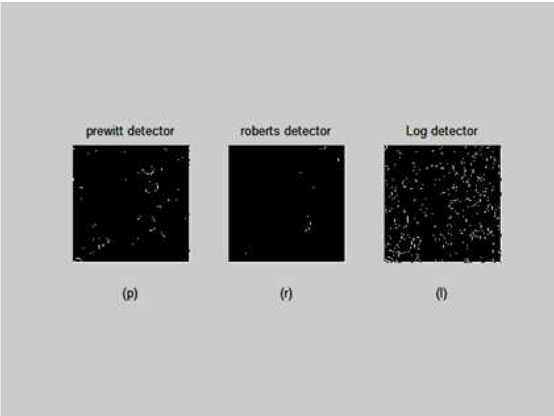

Fig1-b: (P) Prewitt, (r) Roberts, (l) Log

Fig. 1: Material image1

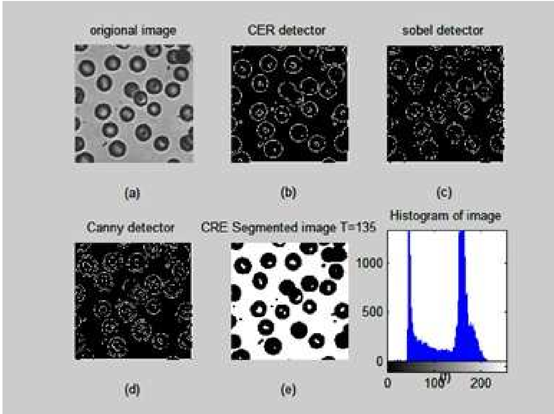

Fig2-a: (a) original, (b) CRE (proposed method), (c) Sobel, (d) Canny, (e) CRE Segmented Image (T =135), (f) Histogram

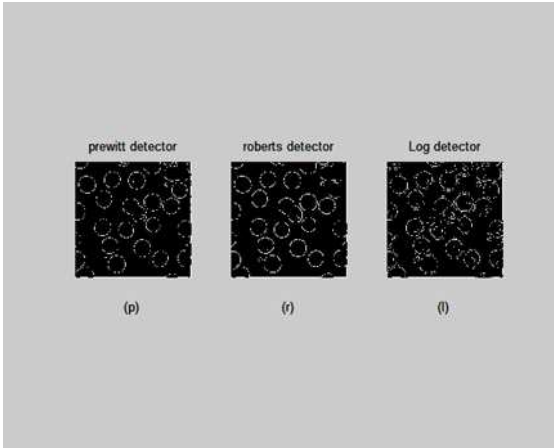

Fig2-b: (P) Prewitt, (r) Roberts, (l) Log

Fig. 2: Material image2

2.2 Edge Algorithm

We introduce the recently-projected edge detection technique based on CRE. First of all a binary image is formed by selecting an acceptable threshold value using (CRE). Secondly, the standard masks are used to find the edges. A spatial filter mask is outlined as a matrix w of size $m \times n$ [27]. For this research paper, we tend to use the smallest important dimension of the mask 3×3 that is outlined as following:
Algorithm CER Edge Detection:

Input: A is image (grayscale) of size M×N and t* value.
Output: image g is the edge detection of A.
Start
Step 1: find a binary image using(CRE) thresholding (t*):
Step 2: find an M×N output image, g:
For each x and y, put g(x, y) = 0.
Step 3: testing for edge pixels:
Use a mask w, with dimensions 3×3:
Step 4: For all $1 \leq x \leq M and 1 \leq y \leq N$:
Create g as an output image by set g = f.
Step 5: for each $2 \leq y \leq N-1 and 2 \leq x \leq M-1$,
Testing for edge pixels:
i. sum = 0;
ii. For all $-1 \leq k \leq 1 and -1 \leq j \leq 1$:
If (f(x, y) = f (x+j, y+k)) then sum= sum+1.
iii. If (sum $>$ 6) Then g(x,y)=0 Else g(x,y)=1 .
End function.

3 Performance measures

In practice, however, subjective evaluation of segmented images is usually too inconvenient, time-consuming and pricy. During this research work, the actual performance of the proposed algorithm and the consistent comparisons are presented. The most common accurate performance measure, peak signal to noise ratio (PSNR) [28] are used. PSNR is measured in decibels

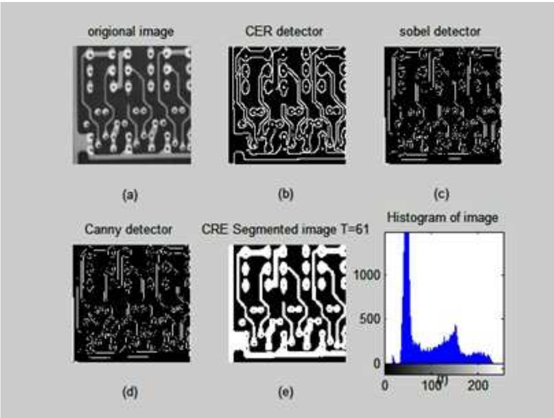

Fig3-a: (a) original, (b) CRE (proposed method), (c) Sobel, (d) Canny, (e) CRE Segmented Image (T =61), (f) Histogram

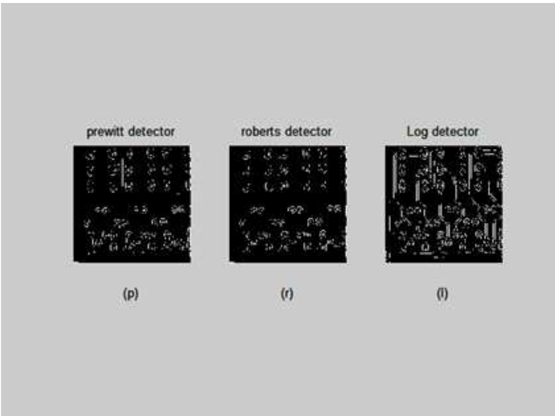

Fig3-b: (P) Prewitt, (r) Roberts, (l) Log

Fig. 3: Material image3

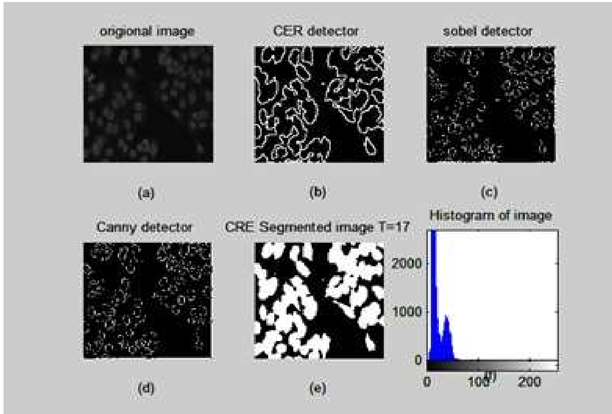

Fig4-a: (a) original, (b) CRE (proposed method), (c) Sobel, (d) Canny, (e) CRE Segmented Image (T =17), (f) Histogram

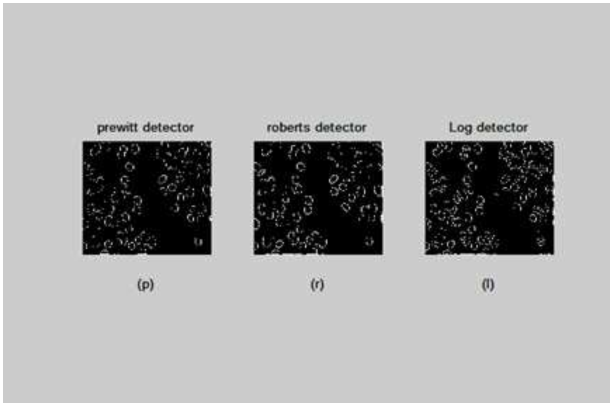

Fig4-b: (P) Prewitt, (r) Roberts, (l) Log

Fig. 4: Cell Image

$$\left.\begin{aligned} PSNR &= 10\log_{10}\left(\frac{255}{RMSE}\right) \\ RMSE &= \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[L(i,j)-S(i,j)]^2}{MN}} \end{aligned}\right\} \tag{9}$$

Where *RMSE* is the root mean-squared error that is defined as above equation.

The S and I are input and output images of size M x N, respectively.

The peak signal to quantitative noise relation (PSNR) is an expression for the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation. It is the logarithmic function of the height value of the image and also the mean square error. Its value must be high. PSNR is used to confirm the quality of the edge images. For the better-threshold image and edge quality, the value of the PSNR measure should be higher.

4 Experimental results

In this experiment, we implement the developed similarity function based on the CRE measure. The performance of the proposed criterion is verified by examining it on NDT and different types of images.

This type of images has a massive category variance distinction within the object and background. Therefore, most of the thresholding and edge methods fail to segment this kind of images [29]. All the used images are 256×256, 8-bit types. The results have been given by the proposed strategies compared to canny, Soble, Prewitt, Roberts, and Log methods. These methods are the most common in the literature. Moreover, the proposed strategies give more accurate results than they do.

4.1 Experiments on NDT images

First, we consider the problem of NDT image analysis. NDT means detecting objects by special instruments and strategies and quantifying their potential defects without

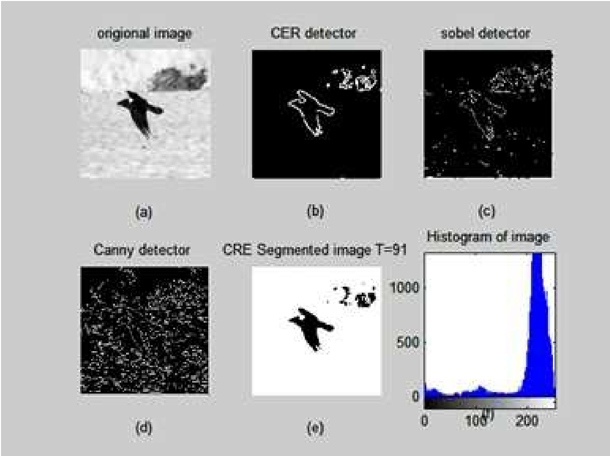

Fig5-a: (a) original, (b) CRE (proposed method), (c) Sobel, (d) Canny, (e) CRE Segmented Image (T =91), (f) Histogram

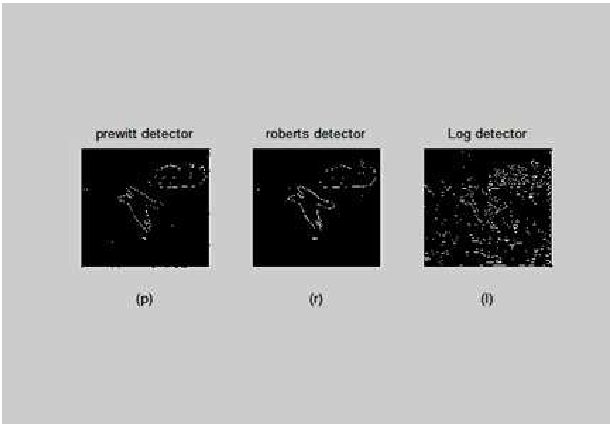

Fig5-b: (P) Prewitt, (r) Roberts, (l) Log

Fig. 5: Real Image 1

harmful effects. NDT employed in an a broad kind of applications in astronautics physical science, and nuclear industry [30]. Three NDT real images examined. The first and second images represent a lightweight research image of a material structure. Lightweight research is often used to inspect the microstructure of a material to obtain information about its properties, such as consistency, particle size, distribution uniformity, and so on. The third one is a Printed Circuit Board (PCB) image. The histogram of gray-scale information is essentially non-Gaussian. The three images are in Figure 1 Where the PSNR for methods CRE, Sobel, Canny, Prewitt, Roberts and Log are 25.9804 25.9798 25.9799 25.9785 25.9784 25.9792 respectively. In Figure 2 , where the PSNR for methods CRE, Sobel, Canny, Prewitt, Roberts and Log is 26.7480 26.7457 26.7460 26.7452 26.7455 26.7459 respectively. Also in Figure 3, where the PSNR for methods CRE, Sobel, Canny, Prewitt, Roberts and

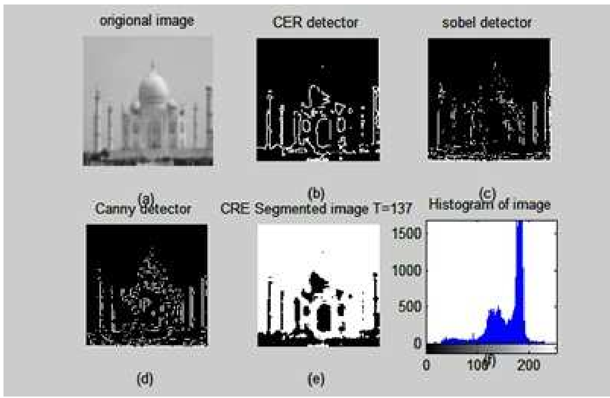

Fig6-a: (a) original, (b) CRE (proposed method), (c) Sobel, (d) Canny, (e) CRE Segmented Image (T =237), (f) Histogram

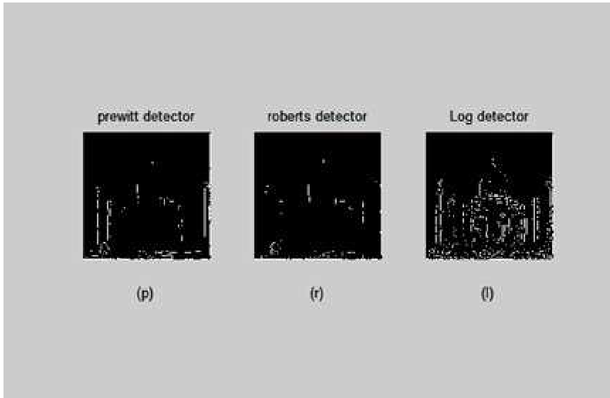

Fig6-b: (P) Prewitt, (r) Roberts, (l) Log

Fig. 6: Real Image 2

Log is 28.1120, 28.1106, 28.1102 28.1082 28.1081 28.1104 respectively.

4.2 Experiments Cell images

The comparison result between CRE (proposal Method) and Sobel, Canny, Prewitt, Roberts and Log methods is shown in Figure 4 for the Cell images, where the PSNR for methods CRE, Sobel, Canny, Prewitt, Roberts and Log is 34.4575 34.4519 34.4524 34.4485 34.4497 34.4511 respectively.

4.3 Experiments Real images

The comparison result between CRE (proposal Method) and Sobel, Canny, Prewitt, Roberts and Log methods for the four Real images with different PSNR value is shown in Figure 5, ,where the PSNR for methods CRE, Sobel, Canny, Prewitt, Roberts and Log are 24.9169 24.9171 24.9185 24.9169 24.9169 24.9175 respectively.In Figure

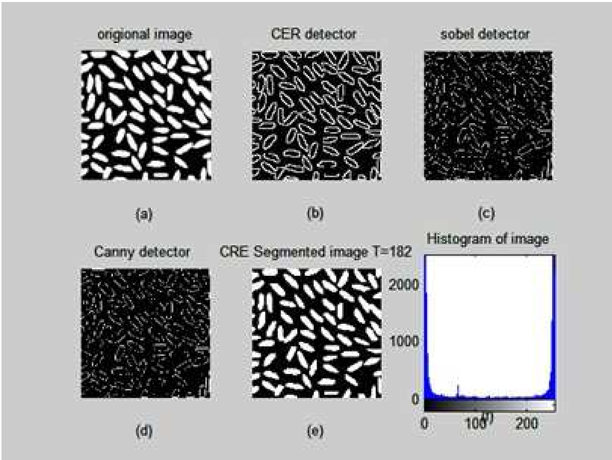

Fig7-a: (a) original, (b) CRE (proposed method), (c) Sobel, (d) Canny, (e) CRE Segmented Image (T =182), (f) Histogram

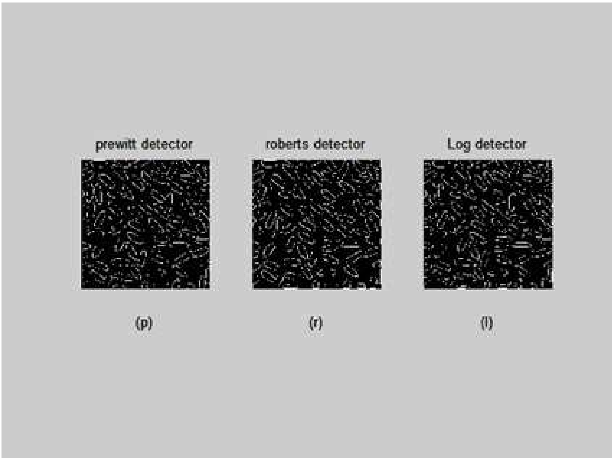

Fig7-b: (P) Prewitt, (r) Roberts, (l) Log

Fig. 7: Real Image 3

6 Where the PSNR for methods CRE, Sobel, Canny, Prewitt, Roberts and Log is 25.9627 25.9619 25.9622 25.9613 25.9612 25.9621 respectively. In Figure 7 the PSNR for methods CRE, Sobel, Canny, Prewitt, Roberts and Log is 26.4815 26.4771 26.4772 26.4770 26.4771 26.4776 respectively. In addition, in Figure 8 the PSNR for methods CRE, Sobel, Canny, Prewitt, Roberts and Log is 26.9461 26.9452 26.9459 26.9448 26.9450 26.9454 respectively.

5 Experimental Results and Discussion

The experimental results are discussed in the following section. The discussion includes the choice of the threshold for the images, and different types of images have been considered. They are real Images, cell images. Table 1 represents the PSNR for CRE, Sobel, Canny, Prewitt, Log, and Robert detectors

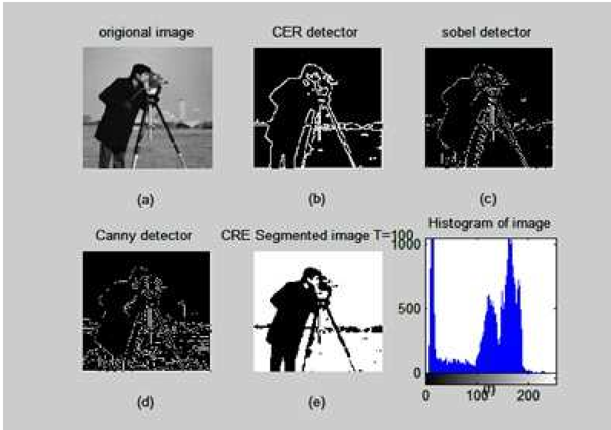

Fig8-a: (a) original, (b) CRE (proposed method), (c) Sobel, (d) Canny, (e) CRE Segmented Image (T =100), (f) Histogram

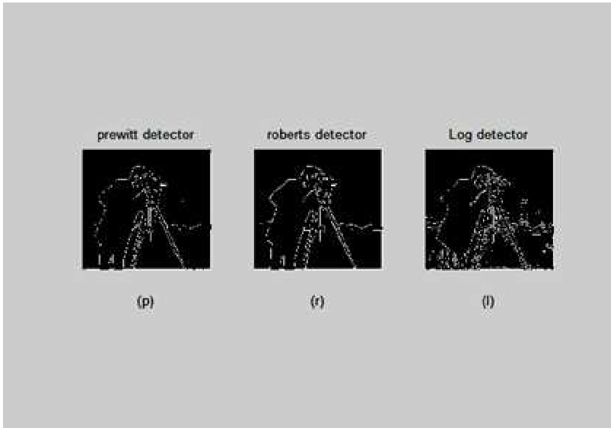

Fig8-b: (P) Prewitt, (r) Roberts, (l) Log

Fig. 8: Real Image 4

Table 1: Values of PSNR for different methods and Images

		CRE	S	C	P	R	L
Material	Image 1	0.9804	0.9798	0.9799	0.9785	0.9784	0.9792
	Image 2	0.748	0.7457	0.746	0.7452	0.7455	0.7459
Cell	Image 3	0.112	0.1106	0.1102	0.1082	0.1081	0.1104
Real	Image 4	0.4575	0.4519	0.4524	0.4485	0.4497	0.4511
	Image 5	0.9169	0.9171	0.9185	0.9169	0.9169	0.9175
	Image 6	0.9627	0.9619	0.9622	0.9613	0.9612	0.9621
	Image 7	0.4815	0.4771	0.4772	0.477	0.4771	0.4776
	Image 8	0.9461	0.9452	0.9459	0.9448	0.945	0.9454
	Average	5.6051	5.5893	5.5923	5.5804	5.5819	5.5892

Table 1 and Figure 9 have shown that the proposed method CRE edge detection works well and better than the five methods, when applied to Material images, cell images and the most of real images, only image5 in the proposed method CER has performed less than canny and log methods.

6 Conclusion

CRE plays a crucial role in statistical mechanics. In this article, we propose an edge detection algorithm based on

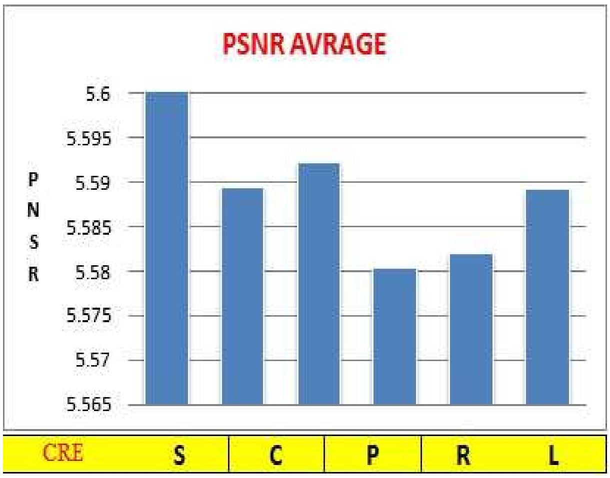

Fig. 9: The chart represents only the average of all decimal part of the PSNR

CRE, however effective methodology of image detection is built on the CRE similarity measure. The projected methodology has the advantage that the strategy is implemented quickly. The CRE edge detection tested on different types of images. Experiments conclude that the CRE edge detection algorithm result is as superior one compared to all for a selected image since different edge detections work better under different conditions. While there are so many edge detection methods in the literature,it becomes a challenging task for experimental communities to distinguish the exact image from the original image without noise.

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M. Al-Shabi received the B.Sc. degree in Computer Science from Technology University at (Iraq) in 1997, the M.Sc. degree in Computer Science from Putra Malaysia University at (2002), and Ph.D. (Computer Science) from Putra Malaysia University, Malaysia (2006). He is currently an associate professor in the Department of Management Information System, College of Business Administration at Taibah University, Kingdom of Saudi Arabia.