# ADAPTIVE ALGORITHM FOR IMAGE CONTRAST ESTIMATION +

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## Abstract

**Image contrasts measuring globally is not efficient tool to estimate image visibility and separate image targets. So in this study we suggest a new algorithm to estimate image contrast by determining the contrast at image edges , where the contrast highly appears in image edge points (i.e. between the pixels of two targets (dark and bright targets)). Also, we study the relation between estimated contrast and the gray levels dynamic range (radiometric resolution), and smoothing process (spatial resolution).**

**It is concluded that the contrast decreases with increasing of number of smoothing iterations and with reduced gray levels dynamic range (i.e. the contrast is reduced with reducing spatial and radiometric resolutions).**

## المستخلص

**إن قياس التباين في الصورة بصورة عامة ليس وسيلة كفؤة لتخمين وضوحها وفصل مناطقها في الصورة . لذا إقترحنا في هذه الدراسة خوارزمية جديدة لتخمين التباين في الصورة وذلك بتحديد أو حساب التباين في مناطق الحافات في الصورة ، حيث يظهر التباين بقوة في مناطق الحافات بين عناصر الصورة في المناطق المختلفة ( أي بين المناطق الداكنة الشدة والفاتحة الشدة ) . و قد تمت دراسة العلاقة بين التباين المخمن ومدى مستويات الشدة الرمادية (الوضوحية الإشعاعية ) وتاثير عملية التنعيم على الوضوحية (الوضوحية الحيزية ) .**

**إستنتجنا في هذه الدراسة أن التباين يقل بزيادة عدد التكرار في عملية التنعيم . ويقل ايضا مع اختزال مدى مستويات الشدة للصورة . وهنا يمكن القول بان التباين ينخفض بانخفاض الوضوحية الحيزية والوضوحية الإشعاعية .**

## Introduction

Image is a description of how the parameter varies over the surface. The standard visual images result from light intensity variations across a two dimensional plane. The image can be formed of the temperature of integrated circuit, blood velocity in a patient's artery, X-ray emission from a distant galaxy, ground motion during an earthquake, etc. These exotic images are usually converted into conventional pictures (i.e. light images), so that they can be evaluated by the human

+Received on 1/12/2004 Accepted on : 14/4/2005
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eye. The images have information encoded in the spatial domain, where the features in the images are represented by edge, not sinusoid. This means that the spacing and number of pixels are determined by how small the features need to be seen rather than by the formal constraints of the sampling theorem[1].

The digital image quality can be measured either objectively, or subjectively. Also, the important parameters can be determined that must be known to describe image resolution. The resolution talks about the digital imaging sensor characteristics. This parameter specifies the ability to distinguish image detail in the spatial domain. Normally spatial resolution is measured by number of pixels per inch, but could be in terms of any other unit of measure[2].

Optically, lenses do not transmit light with one hundred percent efficiency. As light enters the lens, a degradation of contrast occurs. This degradation is typically more visible at a lens full aperture with wide angles, or in image corners. In some situations, degradation is such that vignetting occurs. However, no lens is immune to this phenomenon. The minimum perceptible in the intensity between two adjacent objects in the image, is called contrast resolution. So the contrast resolution measures the ability to distinguish between differences in image intensity[1].

## Digital Image Model

An image is the optical representation of objects illuminated by the light. Since we want to process images using a computer, we represent them as a two dimensional functions of discrete spatial variables. The scalar function f(x,y) can be used to represent the light intensity at each spatial coordinate (x,y). If we assume the coordinates to be a set of positive integers for example x=1,2,3….M, and y=1,2,3,…N, then an image can be presented by a matrix[2,3]:

$$f(x,y)=\begin{bmatrix} f(1,1) & f(1,2) & --- & --- & f(1,N) \\ f(2,1) & f(2,2) & --- & --- & f(2,N) \\ | & | & | & -- & | \\ | & | & | & -- & | \\ f(M,1) & f(M,2) & --- & --- & f(M,N) \end{bmatrix} ----(1)$$

Here this represents an MxN image, and the elements of the matrix are known as pixels. The pixels in digital images are usually taken integer values in the finite range[3,4].

$$\underset{Black}{\min imum\ \text{int} ensity level}\quad 0 \le f(x,y) \le L_{Max}\quad \underset{White}{\max imaum\ \text{int} ensity\ level}\quad ---(2)$$

The interval [0,$L_{Max}$] is known as a gray scale. In this work we study only 8bits gray images (i.e. used 256 distinct values to represent image pixels).

In fact, most cases f(x,y) which we might consider to be the physical signal that impinges on the face of 2D sensor is actually a function of many variables including depth of the objects (z), color (EM-wavelength $\lambda$) and exposure sensing time(t)[4,5].

An image must have the proper brightness and contrast for easy viewing. Brightness refers to the overall lightness or darkness of the image. Contrast is the difference in brightness between objects or regions. For example, low difference in brightness between object and background. That gives a poor contrast, while the high difference in gray levels give a very good contrast.

The adjustment of the contrast and brightness of image can be used to allow different features in the image to be visualized. Brightness and contrast make global changes, which are believable. The bad thing about brightness and contrast is that it does not allow us to position the endpoints of the tonal scale. Tonal detail, which is almost white or almost black, can be shifted to be pure white or pure black by computer lightness moves made with this adjustment.

Evaluating resolution is not enough to guarantee image quality. Several factors like noise, blurring and dynamic gray levels range are very important to ensure image quality[3,4,5].

## Contrast Measures

Many digital contrast enhancement techniques have been used in order to optimize the visual quality of the image for human or machine vision through gray scale or histogram modification [3,4]. All these methods try to enhance the contrast of the input image without measuring the contrast itself.

Contrast measures the relative decrease in the luminance in an image. It is highly correlated to the intensity gradient. Furthermore, the contrast can be defined locally or globally. The local contrast can be estimated depending on the local differences in gray levels of picture elements. Here one can directly define a contrast as a function of image edges. The contrast globally or locally can be given by [6]:

$$C = \frac{I_{\max} - I_{Min}}{I_{Max} + I_{Min}} \qquad -----(3)$$

The efficiency of determining and recognizing image objects (targets), highly depends on image brightness and contrast. But, blurring effect may cause several local distortion in the image edge. This makes the image with poor quality and the separation between the targets very difficulties task. So the measuring of contrast for the whole image plan is not efficient measure to represent the image contrasts or images sharpness. So, we study the image contrast locally in the image. We have proposed a new formulation of the contrast definition based on local image edges. This method is less sensitive to digitization effects and noise. It is thus useful in discriminating the objects according to their boundaries. So any distortion or blurring in image edges can be measured using contrast formula in image edges.

## <u>Contrast Measure Based on Image Edge Algorithm</u>

The suggested algorithm propos a new definition of the image contrast (visibility) based on detected object edge. In this study we use binary image (two targets image), to measure the contrast globally for all image based on local contrast between the two image targets. Also, we study the relation between image contrast and the available dynamic range. This is done by converting image gray levels range by using the following eq.:

$$g(x,y) = round\text{-}integer\left(\frac{f(x,y)-\min}{\max-\min} * (Max - Min)\right) + Min \quad ------(4)$$

Where f(x,y) is original image of dynamic range of gray level values in interval [min,max], and the g(x,y) represents the output image with converted dynamic range to interval [Min,Max], here the values of min, max, Min, and Max are integer values.

For the original image f(x,y), min=0, and max=255 , and with contrast C=1 calculated from eq(3) while the resulting images with gray levels range intervals are as follow:

a) Image1 with interval [Min=40, Max=215] with global contrast C=0.68627.
b) Image2 with interval [Min=80, Max=175] with global contrast C=0.37254.

The contrast is computed from eq(3). From this one can explain the relation between global image contrast and the difference value between image targets (reduce radiometric resolution) , where, we can show that the values of contrast highly decreases with highly decreases in image dynamic range, this makes the separation between image targets very poor.

Also, we study the reducing the spatial resolution and its effect on the image contrast locally between image targets this based on image edge. Were performed smoothing process is by using mean filter to reduce image spatial resolution. This has been done by adopting several sliding mean masks (3x3, 5x5, and 7x7), with using several iterations of smoothing process (2 and 4) iterations. For determining image edges we have adopted Soble operator with masks given below[3].

| | | |
|---|---|---|
| **1** | **2** | **1** |
| **0** | **0** | **0** |
| **-1** | **-2** | **-1** |

| | | |
|---|---|---|
| **1** | **0** | **-1** |
| **2** | **0** | **-2** |
| **1** | **0** | **-1** |

The determined edges in the images use fixed threshold for all cases. The algorithm of the suggested technique is given as follows:

**The Algorithm of Measure Image Contrast ( C ) based on Image Edges**

*Start algorithm* ***Begin***

a. *Set dimensions for original image array img( ), for smoothed image array simg( ) and for edge image array edg( ) (note, all these matrix img(),simg(), and edg() have same dimensions).*
b. *Load image img() from file then find image edge matrix edg() from using Soble edge detection method, and determine 0 for non-edge pixels and 255 for edge pixels.*

*Determine Number of Smoothing iterations (nit).*

*Start loop* ***for itr=0 to nit do begin***

c. *Determine the maximum (max) image pixel value and minimum (min) pixel value in the image edge pixels (i.e. find the max value and min value of img(x,y) when edg(x,y)=255 where (x,y) represent the location of image pixel belong to edges ).*
d. *Compute the contrast C from eq.3. Then print the iteration number itr and the contrast value C.*
e. *Perform mean filter for the img(). (Here the input image is img() matrix and the output image is simg() matrix).*
f. *Put img()=simg().*

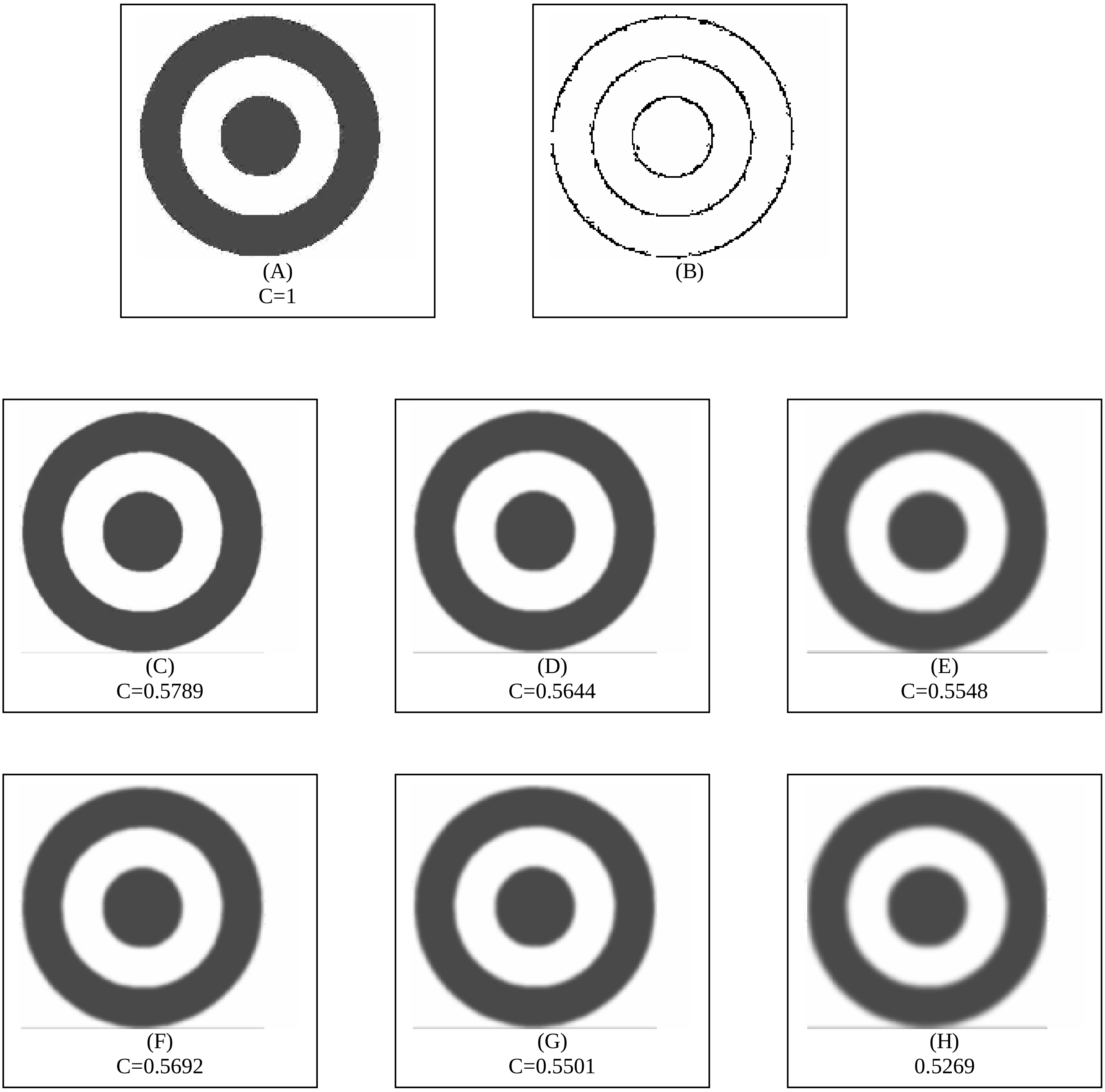
***End (for loop).***

***End.*** *Algorithm*

## Results and Discussions

In this study we adopt binary image (circles) of the original image of dynamic gray levels (0-255) Fig(1:A). Then from this image and by using eq.4 we generate two binary images of dynamic gray levels with ranges of (40-215)Fig(2:A), and range (80-175) Fig(3:A). This is done to reduce image contrast by reducing the global image gray values range, where global contrast of (1, 0.6862, and 0.3725) is obtained for the generated image respectively. The determined edges for the three images based on Soble operator the edge images are shown in Figs(1,2, and 3:B) for the original images of global contrast (C=1, C=0.6862, and C=0.3725) respectively. The smoothing process by using mean filter, is performed by adopting two and four smoothing iterations, for the original images, by using bock sizes (3x3, 5x5,and 7x7)see Figs(1,2,and 3).

The contrast measuring results for all the version images are estimated from applying the suggested algorithm. Here it can be noted that the smoothing processing reduces the spatial resolutions. So can be assume that the number of smoothing iterations as a function of reducing image spatial resolutions. Also, the spatial resolution is highly reduced in edge image regions, when using large smoothing block size like (7x7). The estimation of image contrast is based on image edges, as a function of gray levels dynamic range and of number of smoothing iterations, and smoothing block size. From the results shown in Fig(4), it can be concluded that the contrast decreases with reducing image gray levels range, and also, decreases with performing smoothing process, and increasing the block of smoothing process.

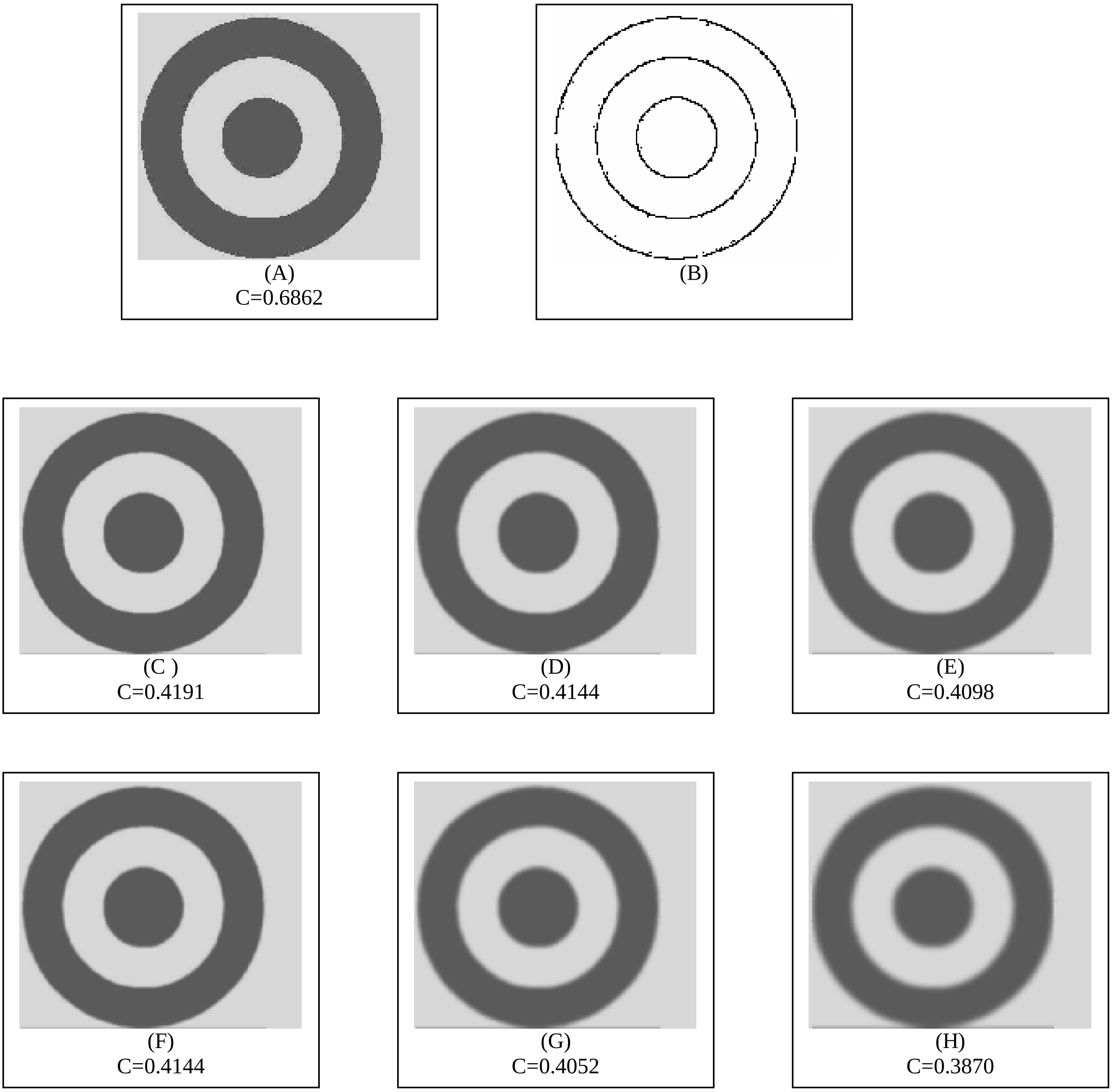



**Fig(1)** A): Original Image( 0-255)gray levels of global contrast=1.

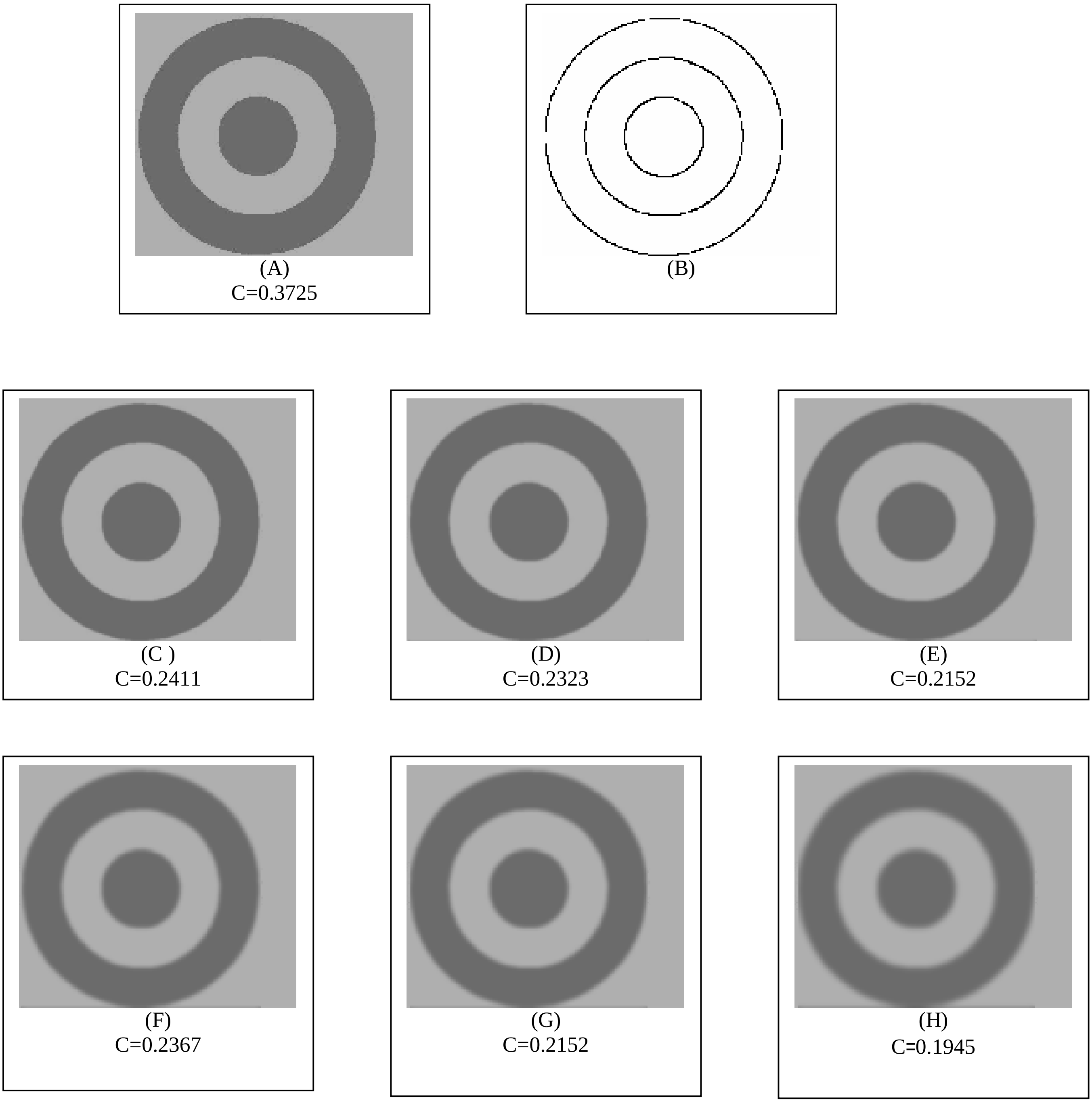
B): Soble Edge of Image of (A).

C,D, and E ) Smoothed Images by using 2iterations of Mean filter Using block size ( 3x3, 5x5, and 7x7) respectively.

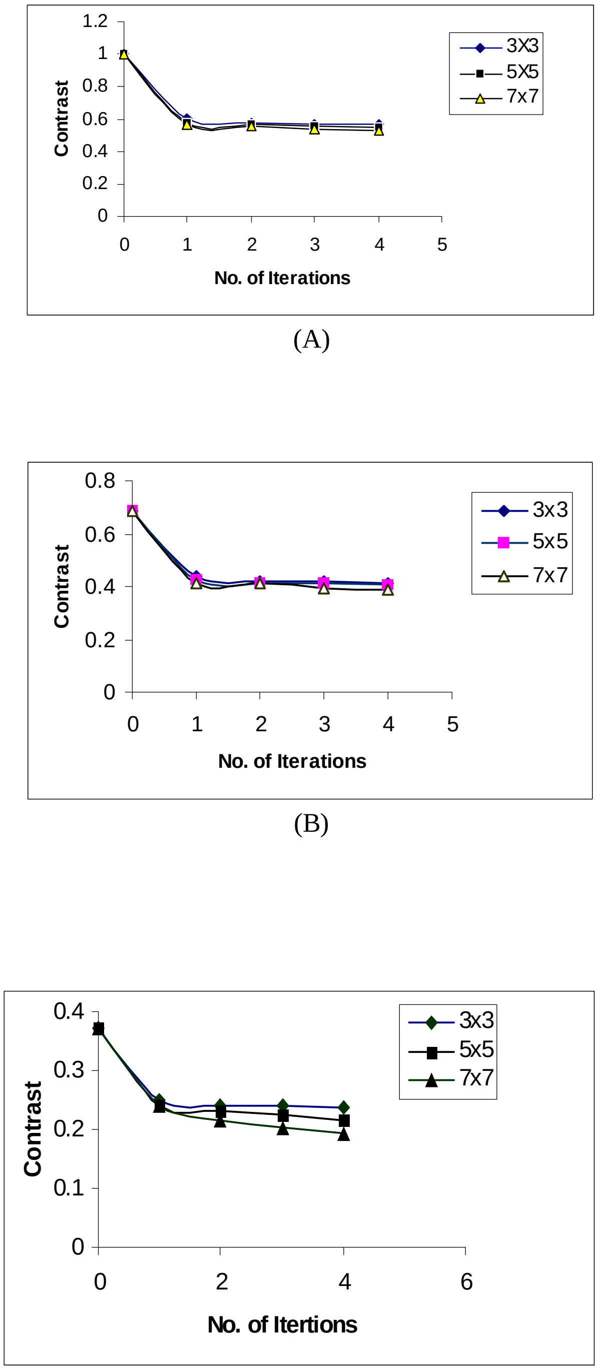
F,G, and H ) Smoothed Images by using 4iterations of Mean filter Using block size ( 3x3, 5x5, and 7x7) respectively.




**Fig(2)** A): Original Image( 40-215)gray levels of global contrast=0.6862.
B): Soble Edge of Image of (A).
C,D, and E ) Smoothed Images by using 2iterations of Mean filter Using block size ( 3x3, 5x5, and 7x7) respectively.
F,G, and H ) Smoothed Images by using 4iterations of Mean filter Using block size ( 3x3, 5x5, and 7x7) respectively.




**Fig(3)** A): Original Image( 80-175)gray levels.
B): Soble Edge of Image of (A).
C,D, and E ) Smoothed Images by using 2iterations of Mean filter Using block size ( 3x3, 5x5, and 7x7) respectively.
F,G, and H ) Smoothed Images by using 4iterations of Mean filter Using block size ( 3x3, 5x5, and 7x7) respectively.




(A)



(B)



(C )

**Fig(4)**:The relation between number of smoothing iterations and estimated contast for images of gray levels dynamic ranges:

A) Image Range (0-255).

B) Image Range (40-215).

C) Image Range (80-175)

**References**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