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# A Novel Method for Edge Detection using Block Truncation Coding and Convolution Technique for Magnetic Resonance Images (MRI) with Performance Measures

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**Abstract:** In this paper, we propose a novel method to detect edges in digital images. Attention is given to magnetic resonance images (MRI) of the brain in particular. Edge detection using block truncation coding and convolution technique are presented. The results are compared with the standard edge detection Canny method . The results of this study are presented and discussed.

**Keywords:** Human brain, MRI, edge detection, block truncation coding, Canny edge detection.

## INTRODUCTION

Edge detection is an important processing in many image processing in medical images, satellite image, in automatic extraction image features etc. There are several standard edge detecting operators, such as Prewit, Robert, Sobel, Laplacian, Canny etc[1] . In medical imaging modalities, Magnetic Resonance Imaging(MRI) is an important technique to image the image of organs in a human body. MRI is widely used to image human brain.

Segmenting brain portion from the slices of MRI is an important process for MRI processing. The conventional edge detectors used for edge detection cannot be used for detecting boundaries in the MRI slices. Special methods are needed to detect the macro and micro edges in the MRI slices. In this paper, we propose a novel method to find edges in a MRI slice using Block Truncation Coding(BTC) used for lossy image compression. We also use frequency domain filtering using convolution and find the boundary in an MRI slice. There is not a single edge detection algorithm that can successfully discover edges for varied images and no specific quantitative measure of the quality exists for edge detection. An effort is made to overcome the above mentioned drawbacks and this method gives an appreciable result for MRI images.

## DIFFERENT EDGE DETECTION TECHNIQUES

There are many ways to perform edge detection. However, they may be primarily grouped into two categories, gradient and Laplacian. The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image. The Laplacian method searches for zero crossings in the second derivative of the image to find edges.[4]

Edges are places in the image with strong intensity contrast. Since edges consist of mainly high frequencies, we can detect edges by applying a high pass frequency filter in the Fourier domain or by convolving the image with an appropriate kernel in the spatial domain. In practice, edge detection is performed in the spatial domain, because it is computationally less expensive and often yields better results. Since edges correspond to strong illumination gradients, we can highlight them by calculating the derivatives of the image.

## BLOCK TRUNCATION CODING (BTC) ALGORITHM

As we know, the BTC is a simple and fast scheme for digital image compression. To detect an edge boundary using the BTC scheme, the bit plane information of each BTC-compressed block is exploited, and a simple block type classifier is introduced.[2] The experimental results show that the proposed scheme clearly detects the edge boundaries of digital images while requiring very little computational complexity

### *Algorithm for BTC*

A. Divide the image into 4X4 block size.
B. Find the mean of the pixels in the block
C. Replace all pixels with value > mean as 1 and others as 0. We will get 16 bits either as 0 or 1, which is called the bit plane.
D. Repeat it for all blocks
E. Combine all the bit planes for each block and join them together to get the binary image. This will give all edges in the image

After implementing this algorithm we can find that edges are detected. However there are many edges and are not of good clarity.

## RESULTS OF BLOCK TRUNCATION CODING (BTC) ALGORITHM

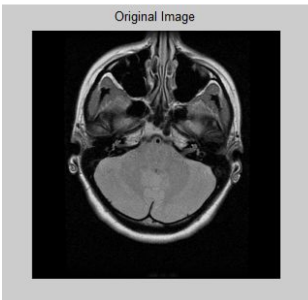


*Fig1*

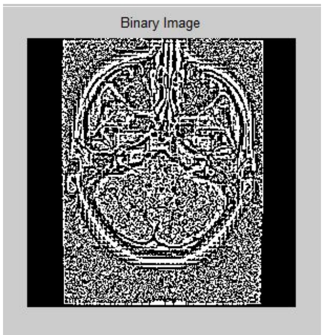


***Fig 2***

## CONVOLUTION METHOD

This is an edge detection operation in which two-dimensional convolution of an input array with the special matrix occurs. The special matrix is like [1 2 1, 0 0 0, -1 -2 -1] which helps such that a gradual increase and decrease in value helps to detect edges. Wherever difference in value is found, it means an edge is present. The special matrix can be scaled to any value but the gradual increase and decrease must be present for clarity of edges. Convolution is used to implement linear operations on images such as frequency filtering of signals, smoothing of images, and enhancement of images[5]. In the Convolution method two arrays of numbers, generally of different sizes, but of the same dimensionality, are multiplied to produce a third array of numbers of the same dimensionality. One of the input arrays is a gray level image or the original MRI image. The second array is known as the special matrix or the kernel.

The convolution is performed by sliding the kernel over the image, starting at the top left corner, so as to move the kernel through all the positions where the kernel fits entirely within the boundaries of the image. Each kernel position corresponds to a single output pixel, the value of which is calculated by multiplying together the kernel value and the underlying image pixel value for each of the cells in the kernel, and then adding all these numbers together

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $I_{11}$ | $I_{12}$ | $I_{13}$ | $I_{14}$ | $I_{15}$ | $I_{16}$ | $I_{17}$ | $I_{18}$ | $I_{19}$ |
| $I_{21}$ | $I_{22}$ | $I_{23}$ | $I_{24}$ | $I_{25}$ | $I_{26}$ | $I_{27}$ | $I_{28}$ | $I_{29}$ |
| $I_{31}$ | $I_{32}$ | $I_{33}$ | $I_{34}$ | $I_{35}$ | $I_{36}$ | $I_{37}$ | $I_{38}$ | $I_{39}$ |
| $I_{41}$ | $I_{42}$ | $I_{43}$ | $I_{44}$ | $I_{45}$ | $I_{46}$ | $I_{47}$ | $I_{48}$ | $I_{49}$ |
| $I_{51}$ | $I_{52}$ | $I_{53}$ | $I_{54}$ | $I_{55}$ | $I_{56}$ | $I_{57}$ | $I_{58}$ | $I_{59}$ |
| $I_{61}$ | $I_{62}$ | $I_{63}$ | $I_{64}$ | $I_{65}$ | $I_{66}$ | $I_{67}$ | $I_{68}$ | $I_{69}$ |

***Table 1***

| | | |
|---|---|---|
| $k_{11}$ | $k_{12}$ | $k_{13}$ |
| $k_{21}$ | $k_{22}$ | $k_{23}$ |

***Table 2***

So, in our example, the value of the bottom right pixel in the output image will be given by:

$$O_{17} = I_{17}K_{11}+I_{18}K_{12}+I_{19}K_{13}+I_{27}K_{21}+I_{27}K_{22}+I_{29}K_{23}$$

If the image has $M$ rows and $N$ columns, and the kernel has $m$ rows and $n$ columns, then the size of the output image will have $M - m + 1$ rows, and $N - n +1$ columns

Mathematically we can write the convolution as:

$$\mathbf{O(i,j)} = \sum_{k=1}^{m} \sum_{l=1}^{n} I(i+k-1,\ j+l-1)\,k(k,l)\,.$$

where $i$ runs from 1 to $M - m + 1$ and $j$ runs from 1 to $N - n + 1$[6]. In order to calculate the output pixel values for the bottom and right edges of the image, it is necessary to select zero value for input pixel where the kernel extends off the end of the image., but this can often distort the output image at these places. Removing $n - 1$ pixels from the right hand side and $m - 1$ pixels from the bottom will clip the image and removes the spurious regions.

## ALGORITHM FOR EDGE DETECTION USING CONVOLUTION TECHNIQUE

A. Calculate the mean of the image block
B. Apply convolution algorithm for the image block as per equ 1 .
C. Display the final image

## RESULTS OF CONVOLUTION TECHNIQUE

Results display the original image in fig 3 and the final image in fig 4 after applying the convolution technique. After implementing this algorithm the edges are detected and are improved in comparison with the previous method.


***Fig 3***

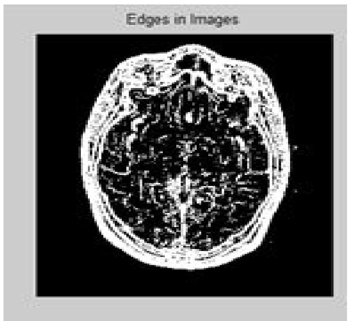


***Fig 4***



 

***Canny Method***

The Canny method finds edges by looking for local maxima of the gradient of I[7]. The gradient is calculated using the derivative of a Gaussian filter[8]. The method uses two thresholds, to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges.[9] After implementation using this method, it was found that it is likely to detect strong edges as well as true weak edges

***Results show standard edge detection technique using canny method.***

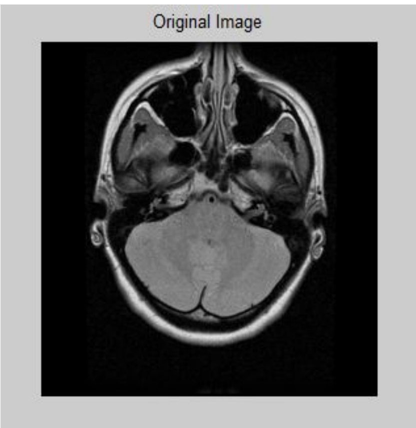


***Fig 5***

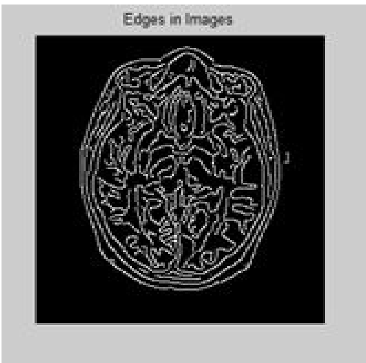


***Fig 6***

**RESULTS AND DISCUSSIONS**

Conventional edge detectors used for edge detection cannot be used for detecting boundaries in the MRI slices and have the following drawbacks.

- They cannot successfully discover macro edges for MRI slices
- Specific quantitative measure of the quality does not exist for edge detection.
- They are computationally Intensive Algorithms.

The proposed system successfully discovers macro edges or boundaries from MRI slices for segmentation of brain regions. It also reduces Image noise, in-homogeneities, and discontinuities of boundaries.

After comparing with many algorithms for edge detection , it is found that after using Canny method which is the best conventional technique, morphological dilation and erosion techniques are used to get the macro edges.[4] These edges form the basis for segmentation. However the same macro edges are seen even after applying Block truncation coding (BTC). The BTC method is fast, requires very little extra memory, easy to implement and has low computational demand [10].

In BTC, the input image is broken into small blocks of size 4x4 pixels. The mean *x* and the standard deviation *σ* are computed for each block using the Eq.(1) and Eq.(2) respectively

$$\bar{x} = \frac{1}{K}\sum_{i=1}^{k} x_i \qquad (1)$$

$$\sigma = \sqrt{\frac{1}{k}\sum_{i=1}^{k}(\bar{x} - X_i)^2} \qquad (2)$$

Each pixel value $x_i$ of the block is compared against the mean value $\bar{x}$ . If the pixel value is greater than or equal to mean, it is coded as 1 else it is coded as 0. The bitplane of size 16 bits of the block is generated using the Eq.(3) as follows,

*if* $x_i \geq \bar{x}$ then 1 else 0.----Eq(3)

For each block of pixels, the bit-plane, the two quantizing levels $q_1$ and $q_2$ are transmitted or stored. This leads to a bit rate of 2 bits per pixel (bpp). A straight forward coding of *x* and *σ* by *m* bits yields a bit rate of,

$$\frac{k + m + m}{k} = 1 + \frac{2m}{K} \text{ bits per pixel (bpp).}$$

For measuring the performance two methods are included.

a. SNR
b. Evidence Criteria.

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With respect to SNR, it is slightly high when 4x4 image is taken. It reduces when it is increased to 32x32, and increases exponentially when increased further.

The evidence criteria with respect to P(not detected), P(misdetected) is nil since all edges are detected and no extra edges are seen.

P(E)= P(misdetected)+P(notdetected).

## CONCLUSION

The proposed system successfully discovers macro edges or boundaries from MRI slices for segmentation of brain regions. It also reduces Image noise, in-homogeneities, and discontinuities of boundaries. The same algorithm can be used for other medical images where soft tissue analysis is the criteria.

## REFERENCES

[1]. Gonzalez R. C., and Woods R.E., Digital Image Processsing, Pearson, 3rd Edition,India, 2014.

[2]. Somasundaram K. and Kaspar Raj I., Low Computational Image Compression Scheme based on obsolute Moment Block Truncation Coding , World Academy of Science, Engineering and Technology vol.19 , pp. 166-171,2006

[3]. Chin-Chen Chang, Chih-Yang Lin, Yi-Hsuan Fan. (2008) Lossless data hiding for color images based on block truncation coding. International Journal for Pattern Recognition and Artificial Intelligence, Volume 17, Issue 06, September 2003

[4]. K. Somasundaram and T. Kalaiselvi, "Automatic brain extraction methods for T1 magnetic resonance images using region labeling and morphological operations," Computers in Biology and Medicine, vol. 41, no. 8, pp. 716–725, 2011

[5]. A. H. Zhuang, D. J. Valentino, and A. W. Toga, "Skull-stripping magnetic resonance brain images using a model-based level set," NeuroImage, vol32, no. 1, pp. 79–92, 2006.

[6]. C. Baillard, P. Hellier, and C. Barillot, "Segmentation of brain 3D MR images using level sets and dense registration," Medical Image Analysis, vol. 5, no. 3, pp. 185–194, 2001.

[7]. S. A. Sadananthan, W. Zheng, M. W. Chee, and V. Zagorodnov, "Skull stripping using graph cuts," NeuroImage, vol. 49, no. 1, pp. 225–239,2010.

[8]. H. Zhang, J. Liu, Z. Zhu, and H. Li, "An automated and simple method for brain MR image extraction," Biomedical Engineering Online, vol. 10, no. 1, p. 81, 2011.

[9]. H. Wendland, "Piecewise polynomial, positive definite and compactly supported radial functions of minimal degree," Advances in computational Mathematics, vol. 4, no. 1, pp. 389–396, 1995.

[10]. Kruger .A, "Block Truncation Compression", Dr. Dobb's Journal, pp.48-55 and pp.104-106, 1992.



 