

EFFICIENT EDGE DETECTION USING SIMPLIFIED GABOR WAVELETS APPLIED TO BRAIN MRI

¹Dr. K.Valarmathi,

¹ professor,

Department of Electronics and Communication Engineering,
PSR Engineering College, Sivakasi, Tamil Nadu

Abstract: GABOR wavelets (GW) are commonly used for edge detection. Extracting gabor feature is computationally intensive. We propose a simplified gabor wavelets(SGW).SGW achieve a similar performance to that of GW,while runtime required for feature extraction using SGW is faster than GW with the use of fourier transform .SGW provide better performance in terms of detection accuracy and computational complexity

Keywords: wavelets, Fourier transform, edge detection, accuracy, extraction.

I INTRODUCTION

An image may be defined as two dimensional function $F(x, y)$, where x and y are spatial coordinates and the amplitude of F at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y and the amplitude values of F are all finite, discrete quantities, the image is called as a digital image. Image segmentation is a core problem in image analysis and computer vision. The essential goal of segmentation is to decompose an image into parts which should be meaningful for certain applications. Segmentation subdivides an image into its constituent regions or objects. The level to which the subdivision depends on the problem being solve.

II LITERATURE SURVEY

This paper presents a new fuzzy based edge detection algorithm. Each different edge detection method has its own advantages and disadvantages. For example each method detects part of real edges and also some unreal edges. To reduce this effect we have used two different source of information and a fuzzy system to decide about whether each pixel is edge or not. First both gradient and standard deviation values are computed, form two set of edges, utilized as inputs for our fuzzy system. Then fuzzy system decides on each pixel according to fuzzy rules. Finally we have compared results of the proposed algorithm with other algorithms such as Sobel, Robert, and Prewitt. Experimental results show the ability and high performance of proposed algorithm.

Issue

Edge is defined as object border, and extracted by features such as gray, color or texture discontinuities. Luminance and geometrical features, lightening condition and noise volume has a great impact on shaping the edge.

Data collection

Images from natural scenes.

Model

In this paper, at first by two different methods, gradient and standard deviation of pixels value, edges are separately extracted and then based on fuzzy logic, final decision about whether each pixel is edge or not is made. Then defuzzification is done.

Justification

The higher quality and superiority of the extracted edges compared to the other methods such as Sobel, Robert, and Prewitt.

Limitation

To achieve good result, some parameters and thresholds are needed to set experimentally.

III PROPOSED SYSTEM

Research in automatic edge detection has been active because of this topic's wild range of applications in image processing, such as automated inspection of machine assemblies, diagnosis in medical imaging, and topographical recognition. However edge detection is a very difficult task. When viewing an image, humans can easily determine the boundaries within that image without needing to do so consciously. However no single edge detection algorithm, at present, has been devised which will successfully determined every different type of edge. In a multi scale wavelet edge detection algorithm used for lip segmentation. Magnetic resonance image (MRI) is a non-invasive imaging technique which is used in medical applications to produce high quality images of the inside of the human body. This technique is successfully applied to obtain detailed pictures of organs, soft tissues, bones and virtually all other internal body structures. However MRI has become the most sensitive imaging test of the brain and nerve tissues. It provides clear images of the brain stem and posterior brain which allow demonstrating pathological alterations of the nerve tissues and detecting most of the brain disorders. After MRI image acquisition, various post processing algorithms are applied to magnetic resonance images in order to extract more information or enable better visualization of information in magnetic resonance images. Especially, detection of tissue borders is performed, as a process of a great importance while recognition of pathological alterations in MRI images. Conventional edge detection algorithms (e.g., Sobel, Laplace) use magnitude images as inputs and convolve them with gradient masks in order to determine edge strength and direction. Edge-detection method based on discrete wavelet transforms (DWT) combines DWT with other methods to achieve an optimal solution to the edge-detection problem.

In this a method for segmentation of brain tumor has been developed on 2D-MRI data which allows the identification (10-15 minutes operator time) of tumor tissue with accuracy and reproducibility comparable to manual segmentation (2-6 hours operator time) making the automatic segmentation practical reality for malignant tumors. In this scheme, after a manual segmentation procedure the tumor identification has been made for the potential use of MRI data for improving the approximate brain tumor shape and 2D visualization for surgical planning

Issue

Three dimensional segmentation is a reliable approach to achieve a proper estimation of tumor volume. The segmentation can be grouped under: Snakes (Gradient Vector Flow), Level Set Segmentation and Watershed Segmentation

Data collection Brain MRI Images.

Model

Watershed segmentation uses the intensity as a parameter to segment the whole image data set . images are divided into regions using a block-based method. Then each classified block is studied individually by calculating its multiple parameter values. For this instance, the multiparameter features refer to the following three specific features: the edges (E), gray values (G), and local contrast (H) of the pixels in the block being analyzed. The model of the proposed system is as shown in fig 1

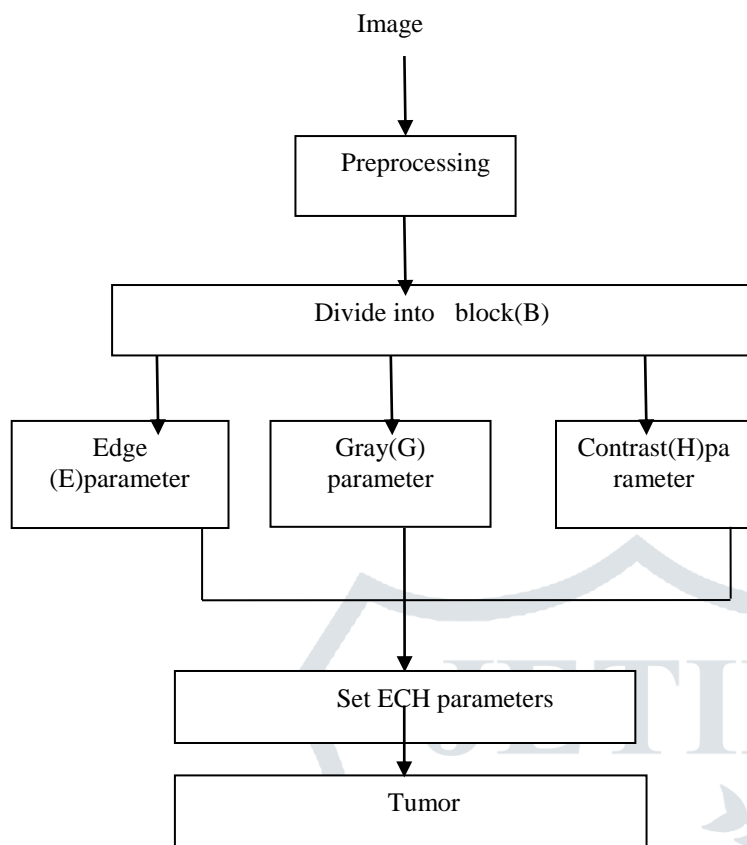


Fig: 1 Block Diagram of Proposed System

Justification

The watershed method did not require an initialization inside the tumor.

Limitation

Watershed Segmentation algorithm performance is better only for the cases where the intensity level difference between the tumor and non tumor regions is higher.

IV COMPARATIVE ANALYSIS OF WAVELET BASED SCALE-INVARIANT FEATURE EXTRACTION USING DIFFERENT WAVELET BASES

Summary

In this paper, classified and comparative study of edge detection algorithms are presented. Experimental results prove that Boie-Cox, Shen- Castan and Canny operators are better than Laplacian of Gaussian (LOG), while LOG is better than Prewitt and Sobel in case of noisy image. Subjective and objective methods are used to evaluate the different edge operators. The morphological filter is more important as an initial process in the edge detection for noisy image and used opening-closing operation as preprocessing to filter noise. Also, smooth the image by first closing and then dilation to enhance the image before the edge operators affect.

Issue

The idea is to examine the distribution of intensity values in the neighborhood of a given pixel and determine if the pixel is to be classified as an edge.

Model

Morphological filtering simplified segmented images by smoothing out object outlines using filling small holes, eliminating small projections. Primary operations are dilation and erosion. There are two methods to evaluate the performance of edge detectors, subjective methods and objective methods. Subjective methods borrowed from the field of psychology and use human judgment to evaluate the performance of edge detectors.

Data Collection

Images from natural scenes.

Justification

In this paper, subjective evaluation of edge detection result images show that Canny, LOG, Prewitt, and Sobel exhibit better performances respectively under noisy conditions. This is because the Gaussian edge detectors are symmetric along the edge and reduce the noise by smoothing the image. The morphological filter is more important as an initial process in the edge detection for noisy image.

Limitation

The Single to Noise Ratio Peak for Canny, Boie-Cox and Shen-Castan are greater than LOG, while LOG is greater than Sobel and Prewitt in case of noisy image.

V Performance comparison

Comparison of the Performances of the SGW Features and the GW Features for Edge Detection is made using the table 2. The use of SGWs for edge detection can save a lot of computation as compared to GWs, while maintaining a level of detection accuracy comparable with the GW. The number of quantization levels used for SGWs is 5. The edge images generated have been post-processed using a thinning algorithm based on morphological operations. so that the edges are of one-pixel width. We consider using $\omega = 0.3\pi$ and $\omega = 0.5\pi$ individually, and then combined in edge detection. In all these cases, the number of orientations is also set at 4. From the different detection results, we see that the relative performances of the SGWs and the GWs with the same centre frequencies and orientations are very similar. In some cases, the detection based on SGWs outperforms the GWs. Actually, the centre frequency of a GW function and its SGW version should be very similar. A SGW is a quantized version of its GW; their rates of variation should be maintained. Hence, in the frequency domain, the centre frequencies of the SGW and the GW should be very close, while the shape of their spectra will differ. In other words, the features extracted using a GW and its corresponding SGW should be similar.

Algorith ms	No. Of Additions	No of Multiplications
Canny	$40 N^2$	$17 N^2$
GW	$48 N^2 + \log 16 N^2$	$32 N^2 + \log 32 N^2$
SGW	$18 N^2$	$16 N^2$

Table: 2 Performance comparison

V RESULTS

5.1 SIMPLE INPUT IMAGE

A simple image as shown in fig 3 is taken as an input for the analysis

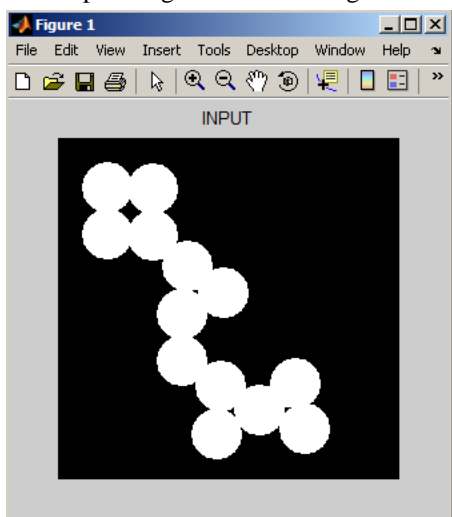


Fig 3 Input image

5.2 OUTPUT IMAGE OF CANNY

The output image at the various stages of processing are obtained. The output image of canny is as shown in fig 4

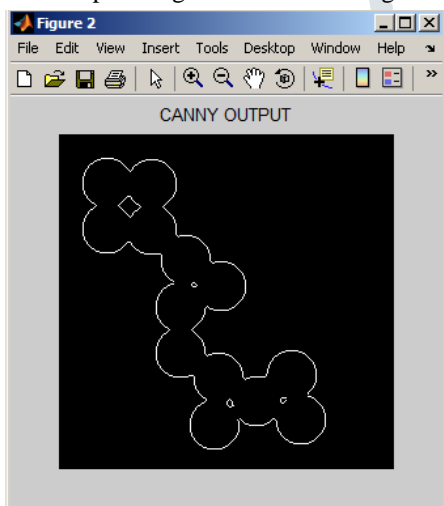


Fig 4 Output image of canny

5.3 OUTPUT IMAGE OF GABOR WAVELETS

The output image of the gabor wavelets is as shown fig 4

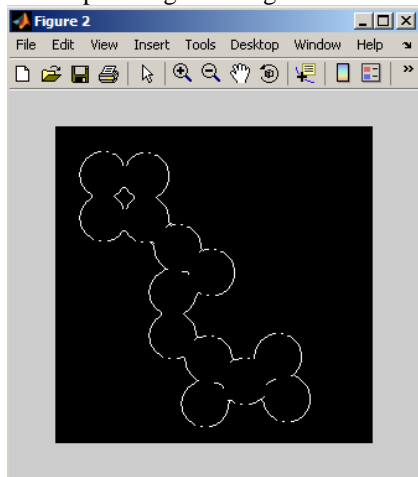


Fig 4 Output image of Gabor wavelets

5.4 OUTPUT IMAGE OF SIMPLIFIED GABOR WAVELETS

The output image of the gabor wavelets is as shown fig 5

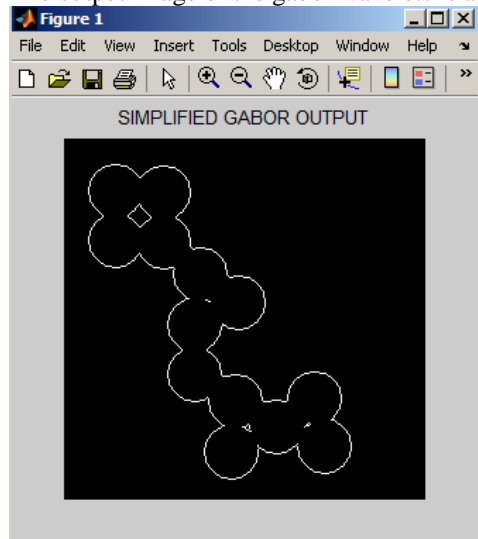


Fig 5 Output image of simplified Gabor Wavelets.

5.5 MRI BRAIN INPUT IMAGE

The MRI brain image used as an input image for the analysis is as shown in fig 6

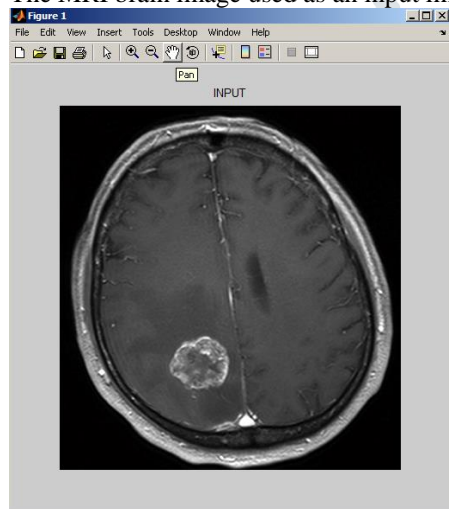


Fig 6 MRI Brain input image

5.6 CANNY OUTPUT FOR BRAIN MRI IMAGE

The output image at various stages are found for the MRI Brain Input Image. The output image for the canny is as shown in fig 7

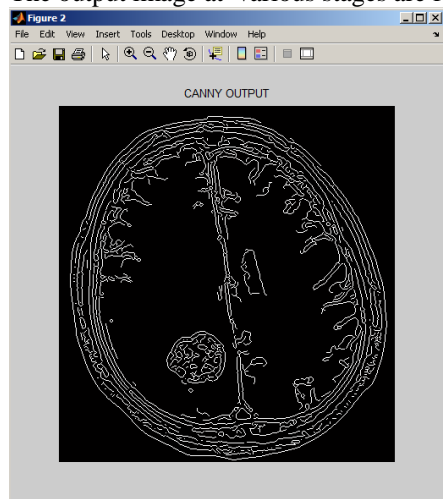
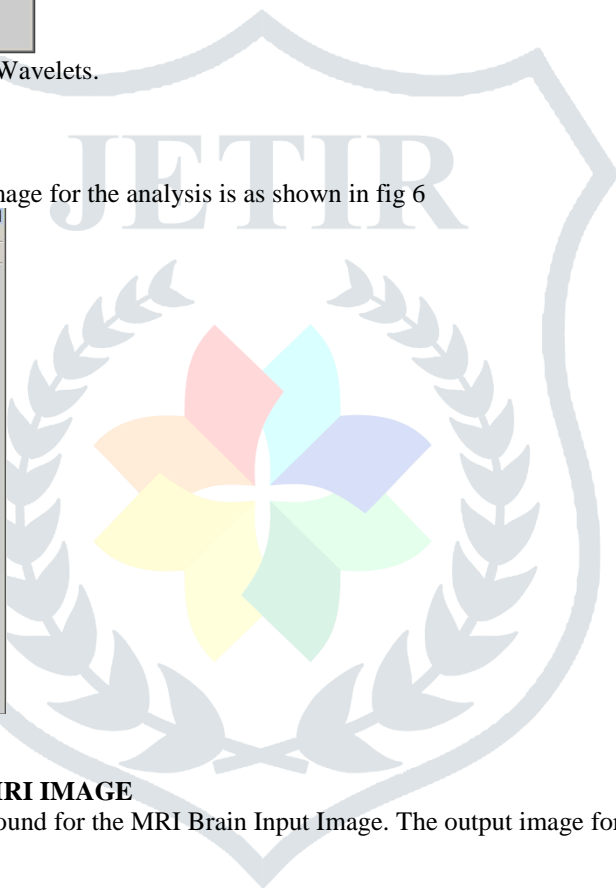


Fig 7 Canny output for brain MRI Image



5.7 GABOR WAVELET OUTPUT FOR BRAIN MRI IMAGE

The output image of the gabor wavelet for the Brain MRI image is as shown in fig 8

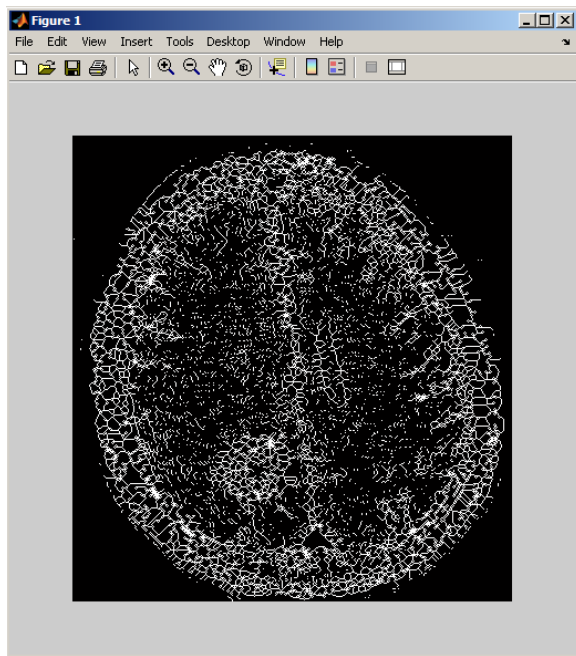


Fig:8 Gabor wavelet output for brain MRI image

5.8 SIMPLIFIED GABOR WAVELET OUTPUT FOR BRAIN MRI IMAGE

Simplified Gabor Wavelet output for Brain MRI Image is as shown in Fig 9

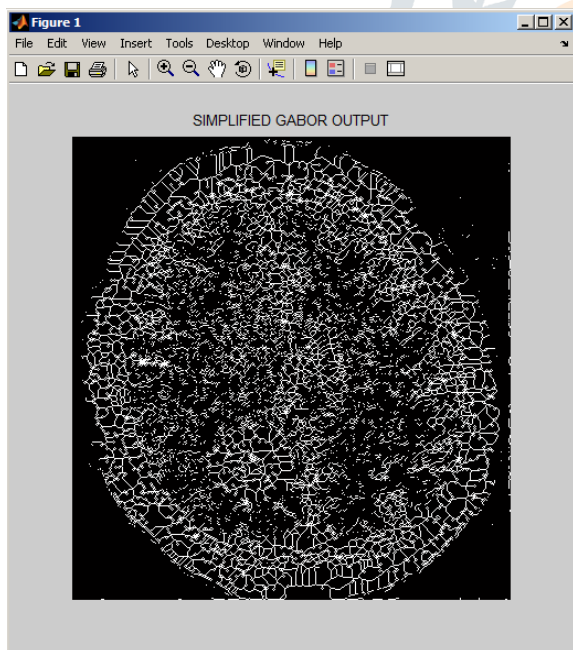


Fig 9 Simplified Gabor Wavelet output for Brain MRI Image

5.9 FCM THRESHOLD OUTPUT TO SIMPLE IMAGE

The FCM threshold output of a simple image is as shown in fig 10

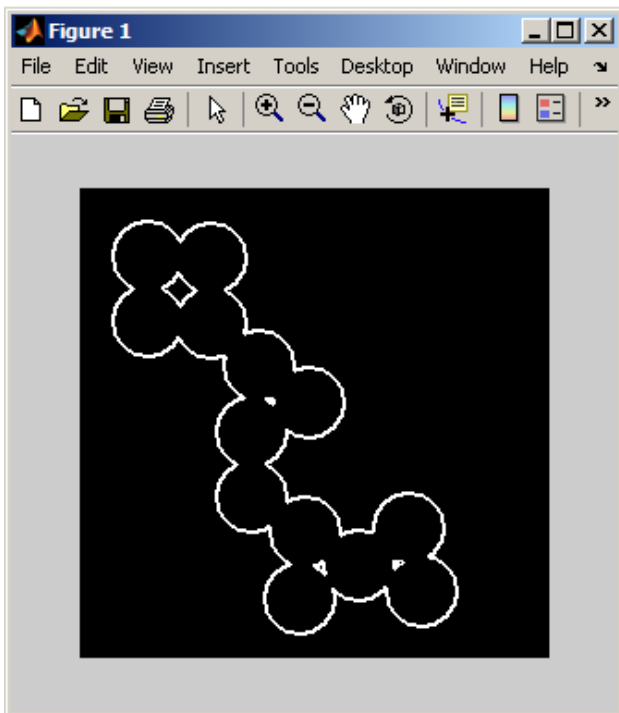


Fig 10 FCM THRESHOLD OUTPUT TO SIMPLE IMAGE

5.10 FCM THRESHOLD OUTPUT TO BRAIN MRI IMAGE

The FCM threshold output of a simple image is as shown in fig 11

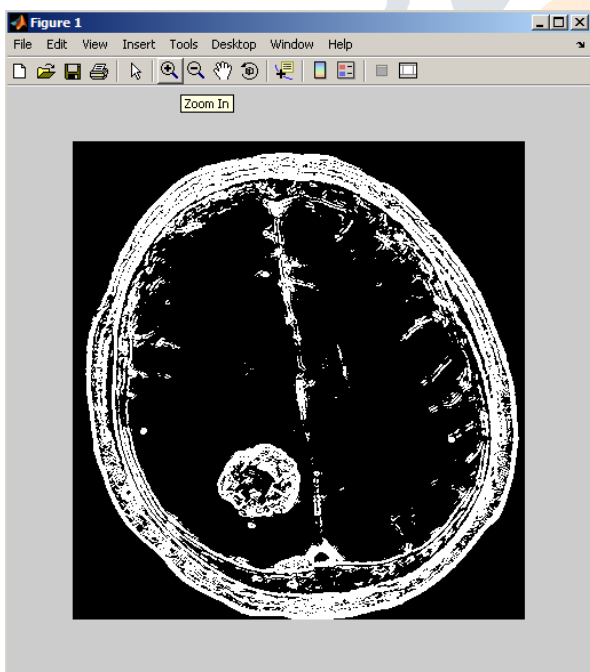
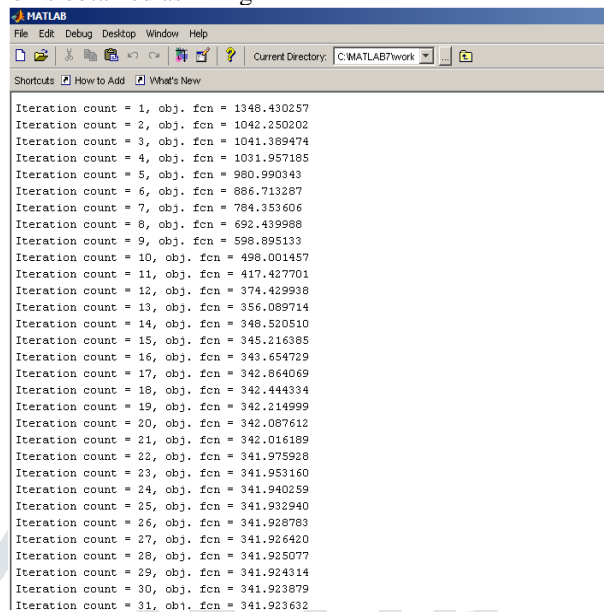


Fig 11 FCM Threshold output to Brain MRI Image.

4.11 ITERATION COUNT FOR FCM THRESHOLD

The iteration count for FCM threshold is obtained as in Fig 11



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MATLAB
File Edit Debug Desktop Window Help
Current Directory: C:\MATLAB7\work
Shortcuts How to Add What's New

Iteration count = 1, obj. fcn = 1348.430257
Iteration count = 2, obj. fcn = 1042.250202
Iteration count = 3, obj. fcn = 1041.369474
Iteration count = 4, obj. fcn = 1031.957185
Iteration count = 5, obj. fcn = 980.990343
Iteration count = 6, obj. fcn = 886.713287
Iteration count = 7, obj. fcn = 784.353606
Iteration count = 8, obj. fcn = 692.439988
Iteration count = 9, obj. fcn = 598.895133
Iteration count = 10, obj. fcn = 498.001457
Iteration count = 11, obj. fcn = 417.427701
Iteration count = 12, obj. fcn = 374.429938
Iteration count = 13, obj. fcn = 356.069714
Iteration count = 14, obj. fcn = 348.520510
Iteration count = 15, obj. fcn = 345.216385
Iteration count = 16, obj. fcn = 343.654729
Iteration count = 17, obj. fcn = 342.864069
Iteration count = 18, obj. fcn = 342.444334
Iteration count = 19, obj. fcn = 342.214999
Iteration count = 20, obj. fcn = 342.087612
Iteration count = 21, obj. fcn = 342.016189
Iteration count = 22, obj. fcn = 341.975928
Iteration count = 23, obj. fcn = 341.953160
Iteration count = 24, obj. fcn = 341.940259
Iteration count = 25, obj. fcn = 341.932940
Iteration count = 26, obj. fcn = 341.928783
Iteration count = 27, obj. fcn = 341.926420
Iteration count = 28, obj. fcn = 341.925077
Iteration count = 29, obj. fcn = 341.924314
Iteration count = 30, obj. fcn = 341.923879
Iteration count = 31, obj. fcn = 341.923632

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Fig 11 Iteration count for FCM Threshold

CONCLUSION

In this paper, it is proposed to use features based on the simplified version of GWs for edge detection, and have introduced the masks for the SGWs at different scales and orientations for feature extraction. Our efficient edge detection algorithm can achieve a performance level in To have an accurate approximation, we set $n = 3$, then terms of detection accuracy similar to that based on GWs, but requires a significantly smaller amount of computation. Our algorithm is also compared to the Canny algorithm and other conventional algorithms, and ours shows a superior performance. The run time is also greatly reduced compared to Canny and Gabor methods and hence speed up rate of 400 times compared to GW and 2 times compared to Canny method has been achieved. The simplified gabor method with FCM threshold is used to segment the MRI brain tumour and successful results have been achieved.

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