MENINGIOMA BRAIN TUMOR EXTRACTION IN MRI IMAGE USING INTEREST POINT GENERATION AND REGION OPTIMIZATION

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Abstract: Medical imaging is uniting of the most complicated and challenging applications of image processing domain. Magnetic Resonance Images (MRI) carry on a notable role in the identification of the disease using computerized examination. The Segmentation process is detection and extraction of an abnormal area of MRI brain image significant. But the process is accurate and time-consuming when the radiologist has more experience in the relevant field. To resolve these complexities, a computerized analysis is required. An efficient tumor extraction method is proposed in this work to improve the performance. The proposed method worked Susan interest point detection for region growing and optimization of the region based on the intensity based regions optimization of the tumor. Modified Median filter, contrast stretching and skull stripping are employed as the preprocessing for the proposed work. The experimental results of proposed technique have been evaluated and validated for performance on magnetic resonance brain images, based on Similarity, Hausdorff distance, Dice and Jaccard. The experimental results achieved better shows the improvement in abnormal tissues, among given MRI images in terms of Segmentation, extraction is compared with existing methods.

Key Words: MRI, interest point detection, region growing, Hausdorff distance, tumor extraction.

1. Introduction:

Images are the depository of information. Basically, image processing process through the image and carry out information which interpreted in it. That valuable information is used to process furthermore various deals [1] [2]. So far, many image processing techniques are used in scientific applications to achieve various dissimilar problem and its solutions.

Medical image processing requires an interdisciplinary field that includes medicine, computer science, electrical engineering, physics, and mathematics. Medical Image processing is aimed at developing systems to solve the medical diagnosis problems using computerized systems that make use of above-mentioned fields of sciences [3]. The computer application programs used in image processing is to extract clinically useful data from medical images. Medical image processing focuses on the computational analysis of the images.

The tumor is described as the growth of abnormal tissues in an uncontrolled manner and it creates a new portion of the tissues in the human body. These unnatural tissues multiplying and create a mass in the brain, that tissues are called a brain tumor or brain cancer [7]. Brain tumors can be considered as either primary brain tumors or metastatic brain tumors. In primary ones, the origin of the cells is brain tissue cells, wherein metastatic ones cells become cancerous at any other part of the body and spread into the brain. [6].

MRI plays a core innovative role in medical imaging [3] [4] [5]. MRI is based on the principle of nuclear magnetic resonance (NMR). Two basic principles of NMR is Atoms with an odd number of protons or neutrons have spin and Another aspect is a moving electric charge, either positive or negative, produces a magnetic field. The body has many such atoms that can act as good MR nuclei. All MRI is hydrogen (proton) imaging. Because Hydrogen is abundant in the body in the form of water and fat. Every hydrogen nucleus is a tiny magnet which produces a small but noticeable magnetic field.

The Region growing method, disjoint regions are formed by absorption of pixels in a neighborhood with uniformity property. Region growing and watershed algorithm are the two methods of the region-based technique [8]. In this method the segmentation is based on the seed points selected on the convenience of the user, then the pixels are analyzed and added to the region then finally the complete area is calculated. The advantage of this method is that segmentation of the regions with similar properties can be done correctly and the connected region is generated. The disadvantage is the reduction of the accuracy because of the incomplete volume effect in the brain images [8] [9]. To overcome this problem, select an accurate seed point to grow the perfect region based on the given threshold value.

The Susan interest point detector does not use spatial derivatives nor smoothes the image. Instead, a circular mask is applied around every pixel, and the grayscale values of all the pixels within the mask are compared to that of the center pixel (the "nucleus") [14] [15]. Calculate the number of pixels within the circular mask which have similar brightness to the nucleus. It is observed that the USAN becomes smaller as it approaches an edge and this reduction is stronger at corners and Susan can thus be used for both line and edge detection. This corner detector computes fast, with good repeatability rate [16].

The proposed method worked Susan interest point detection for region growing and optimization of the region based on the intensity based regions optimization of the tumor. Modified Median filter, contrast stretching and skull stripping are employed as the preprocessing for the proposed work.

The organization of this paper is as follows. Section 2 concisely discusses the background of the study, pre-processing of medical images and proposed works are discussed in Section 3. Section 4 is entirely focused on the results and analysis. Finally, the conclusion is placed in Section 5.

2. Background Study:

2.1. Pre-processing

Preprocessing is an essential step in digital image processing. Because the MRI images are having some impulsive noise or noise generated due to the movement of the patient during the imaging process. The images should be made enhanced for efficient brain tumor detection by the following pre-processing.

- ***Image conversion*** - The image which is used in this research work is in .jpg format. So first convert the image from RGB model to gray-level image.
- ***Resizing of images*** - The converted gray-level image is resized to 400×400 for providing uniformity time consuming.
- ***Image enhancement*** **-** Median filter 3x3 is used to remove the impulsive noise present and to reduce edge blurring effect [11] and Contrast stretching is enrich the contrast.
- ***Skull Removing*** - The skull stripping process removes the non brain tissues. The non brain tissues of skull, CFS, fat and skill are also named as non cortical tissues [12]. In MRI image the skull part is like a ring around the brain tissues. The skull is removed because the intensity value of the skull and tumor is the same. The process results the brain portion alone using mathematical morphological operation and watershed transform [12] [13].

2.2. Region Growing

The basic idea of Region Growing method disjoint regions are formed by absorption of pixels in a neighborhood with uniformity property. In this method the segmentation is based on the seed points selected on the convenience of the user, then the pixels are analyzed and added to the region then finally the complete area is calculated [8]. Seed are selected under the below conditions as follows:

- If only one neighbor is labeled, then the picture element is labeled as the same region as the labeled neighbor.

- If more than one neighbor is labeled and the labels are the same, then the pixel is labeled as the same region as its neighbors are labeled.
- If more than one neighbor is labeled and the labels differ, then the pixel is labeled in the region that has the smallest distance to the pixel

The basic formulation for Region-Based Segmentation is given below.

$$\bigcup_{i=1}^{n} R_i = R$$

R_i is a connected region, i=1,2,3,…,n

$R_i \cap R_j = \phi$

$P(R_i)=$ True for i = 1,2,3..., n

$P(R_i \cup R_j)$ False for any adjacent region R_j

And $R_j \cdot P(R_j)$ is a logical predicate defined

Over the points set $P(R_k)$ and ϕ is the null set.

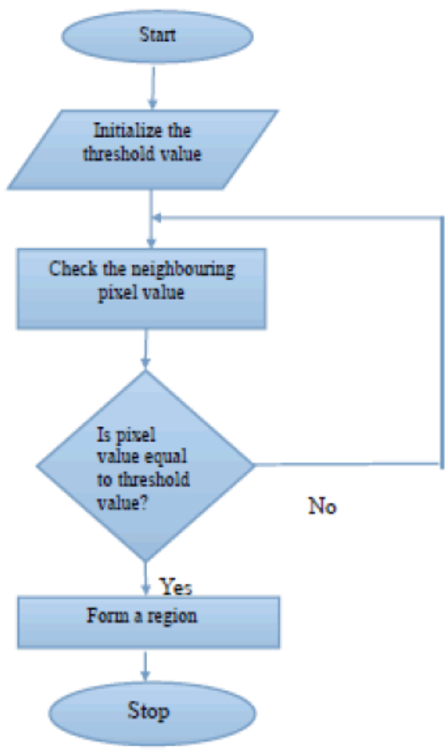

Fig. 1. Region Growing Algorithm

Calculating the average pixel intensity values of the region grown so far is checked with a neighboring pixel intensity value [10]. Considering the first seed point as the primary average, as the region starts to grow, the average is calculated to control the growing procedures. The Region has been set to ROI average value ± a threshold value T.

$$region = Avg(ROI) \pm T$$

2.3 Interest point detection

Interest point(Corner point) is the point whose gray level changes acutely or the cross-point of outline boundary, which reflects the important information in image. Detecting corner point is beneficial to emphasizing the important information in image and weakening the minor information [20]. Compared with other features, such as line, circle, edge, and so on, the detection of corner feature is easy, steady and has good adaptability. One of the most popular method is SUSAN corner detection. Five representative shaped of the USAN are shown in the following Figure.

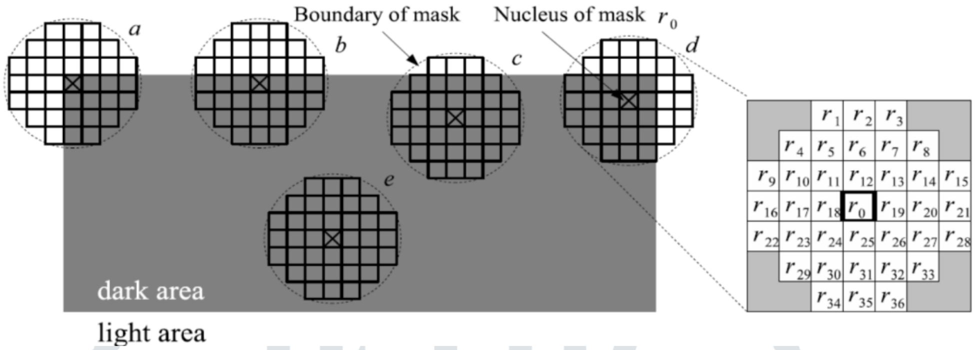

Fig. 2. Five circular masks on different places of an image and the pixels used for USAN calculation

The USAN area reaches the maximum when the nucleus lies in a flat region of the image surface; it falls to half of the maximum when the nucleus is on a straight edge; and falls even further when the nucleus is a corner [17] [18]. The local minima of the USAN map represent the position of image corners. It is this property of the USAN area that is used as the main determinant of the presence of corners. Moving the circular template through each point of the image, the intensity of each pixel within the template is compared with that of the nucleus. A simple equation determined this comparison is as follows[19]:

$$c(\vec{r},\vec{r_0}) = \begin{cases} 1, if |I(\vec{r}) - I(\vec{r_0})| \le t \\ 0, otherwise \end{cases}$$

Where, $I(\vec{r_0})$ is the intensity of the nucleus, $I(\vec{r})$ is the intensity of any other pixel within the template, t is the gray-level difference threshold and $c(\vec{r},\vec{r_0})$ is the output of the comparison. This comparison is done for each pixel within the template [19], and a running total of the outputs $c(\vec{r},\vec{r_0})$ are as follows:

$$n(\vec{r_0}) = \sum_{\vec{r}} c(\vec{r},\vec{r_0})$$

Next, ***n*** is compared with a geometric threshold ***g***. The feature response is created by using the following rule:

$$R(\vec{r_0}) = \begin{cases} g - n(\vec{r_0}), \ \ if \ \ n(\vec{r_0}) < g; \\ 0, \qquad\qquad otherwise \end{cases}$$

3. Methodology:

1. The proposed method is worked in Susan interest point detection for region growing and optimization of the region based on the intensity Similarity between the regions of the tumor.
2. SUSAN operator needs to adjust similarity threshold manually time after time in the process of interest point detection. So we can adjust the threshold value for tumor interest points.

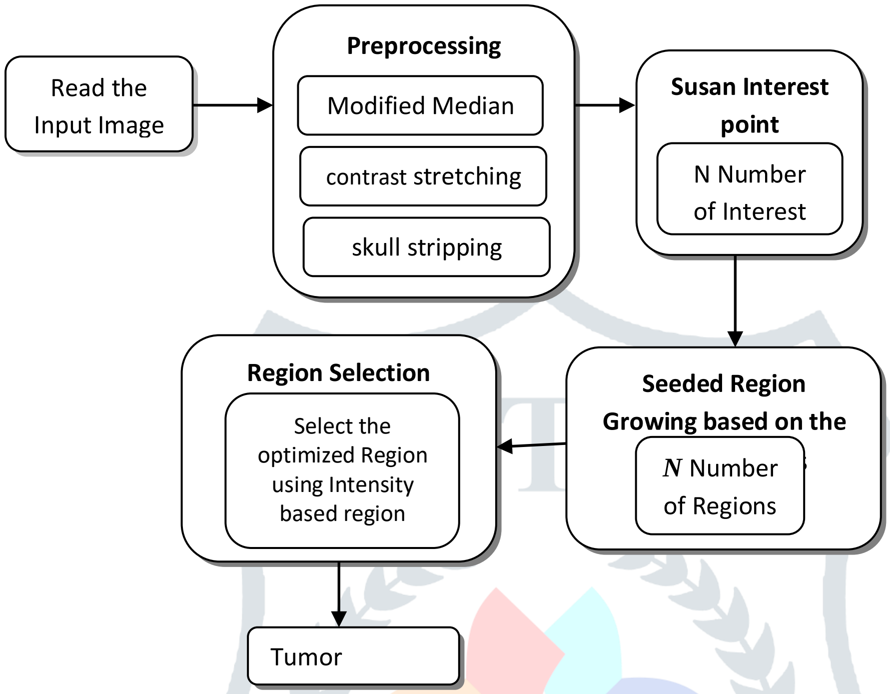

Fig. 3. Flowchart of Proposed Method

3. Few numbers of interest points are detected from the Susan operator. These points are considered as seed points to Region Growing method.
4. Now there are a few numbers of the region from the interest points we can obtain.
5. The intensity-based region optimization technique is performed to select an optimum region from that number of regions. Here already select the interest points are based on the approximate intensity which implies the tumor. So interest points are highlighted on the tumor region. From the few number of interest point an optimum region of tumor is selected based on the following method
   - Calculate the threshold (T) value which is segment the tumor.
   - For every Seed point (x,y) compare, if the intensity value of the seed point nearest to T value.
   - Other seed points are ignored.
6. The experimental results of proposed technique have been evaluated and validated for performance on magnetic resonance brain images, based on Similarity, Hausdorff distance, Dice and Jaccard.

The stepwise implementation is briefly shown in the given below image for better understanding.

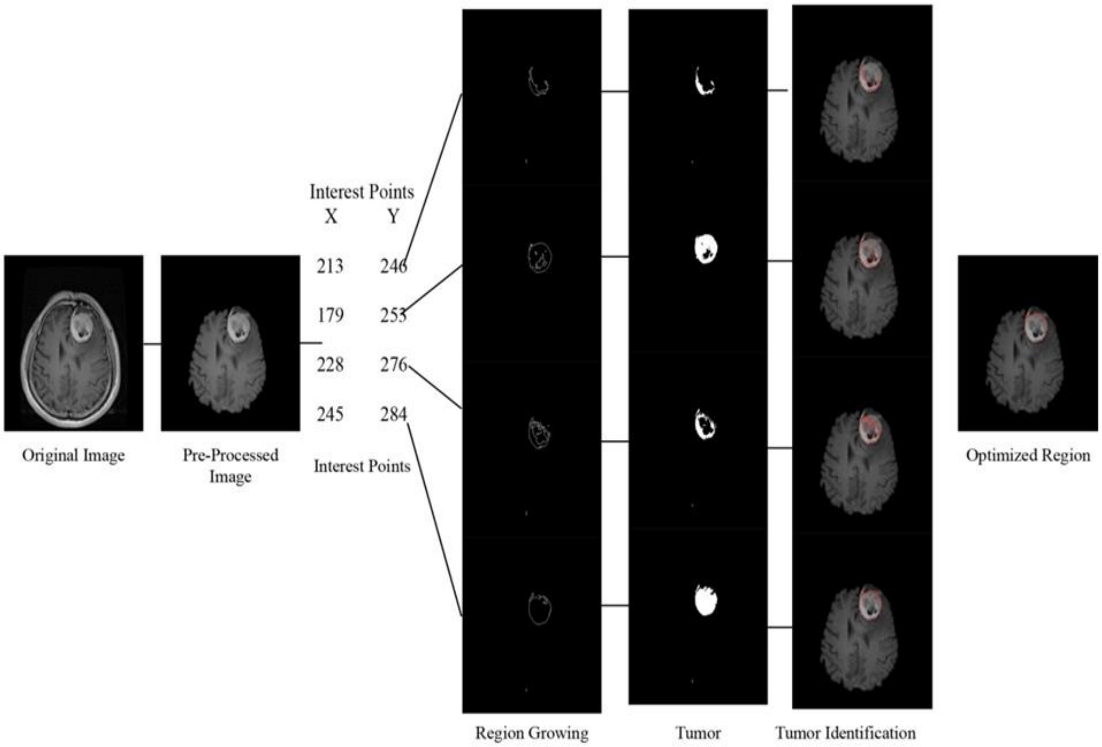

Fig. 4 Stepwise Implementation

4. Validation:

It is important to verify the segmentation method on real MRIs. A validation technique can be a composition of two components. The first one is the ground truth, and the second one is a measure for defining the result deviation from the ground truth.

The experimental results on real and simulated images can be verified with the standard Jaccard similarity index. This metric measures the similarities between the two sets as the ratio of the amount of their intersection divided by the amount of their union [24].

$$JS(S_1,S_2)=\frac{|S_1 \cup S_2|}{|S_1 \cap S_2|}$$

The Structural Similarity Index metric is a comparison of structural information of two images. Ground truth images are used to compare the results. The SSIM is calculated on X, Y axis of an image [23]. The calculation is made between two windows and of common size N×N in following equation.

$$SSIM(X,Y) = l(x,y).c(x,y).s(x,y)$$

Where $l(x,y)$ luminance changes

$c(x,y)$ Contrast change

$s(x,y)$ Structural change

The directed Hausdorff distance *Hag*, between two sets of points *A* and *G* can be obtained in a two stage manner. First, for each point in *A* the minimum distance to all points in *G* is obtained. *Hag* is the maximum of this set of minimum distances [21] [22].

$$HD = \max\{d_i^{ag}\}, i = \{1,..n_a\}$$
$$Hausdorff - Distance = \max(H_{ag}, H_{ga})$$

Table 1 Qualitative analysis values

Methods	Adaptive thresholding			SSRG			Proposed method		
Metrics	Hausdorff distance	Jaccard	SSIM	Hausdorff distance	Jaccard	SSIM	Hausdorff distance	Jaccard	SSIM
Image1	0.9729	0.9617	0.9626	0.9769	0.9717	0.9653	0.9819	0.9721	0.9753
Image2	0.9417	0.9741	0.9429	0.9557	0.9738	0.9492	0.9547	0.9732	0.9530
Image3	0.9592	0.9543	0.9641	0.9572	0.9634	0.9695	0.9598	0.9682	0.9705
Image4	0.9546	0.9612	0.9631	0.9516	0.972	0.9682	0.9562	0.9798	0.9742
Image5	0.9415	0.9737	0.9615	0.9535	0.971	0.9685	0.9545	0.9751	0.9751
Image6	0.9572	0.9717	0.9619	0.9510	0.9634	0.9675	0.967	0.9742	0.9705
Image7	0.9576	0.9742	0.9782	0.9612	0.972	0.9791	0.9626	0.9789	0.9842
Image8	0.9422	0.9621	0.9627	0.9531	0.971	0.9721	0.9625	0.9786	0.9751

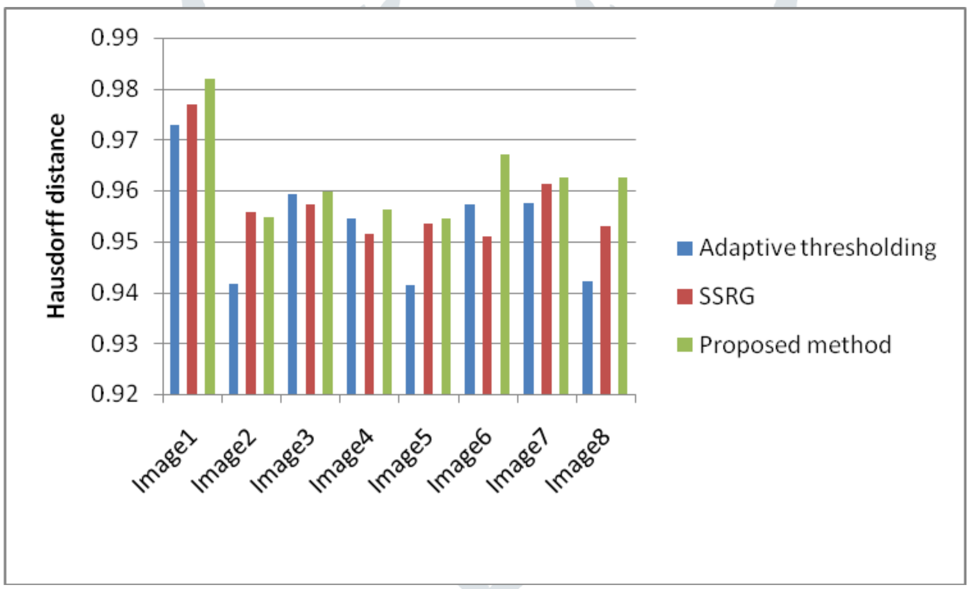

Fig 5. Hausdorff distance Bar chart

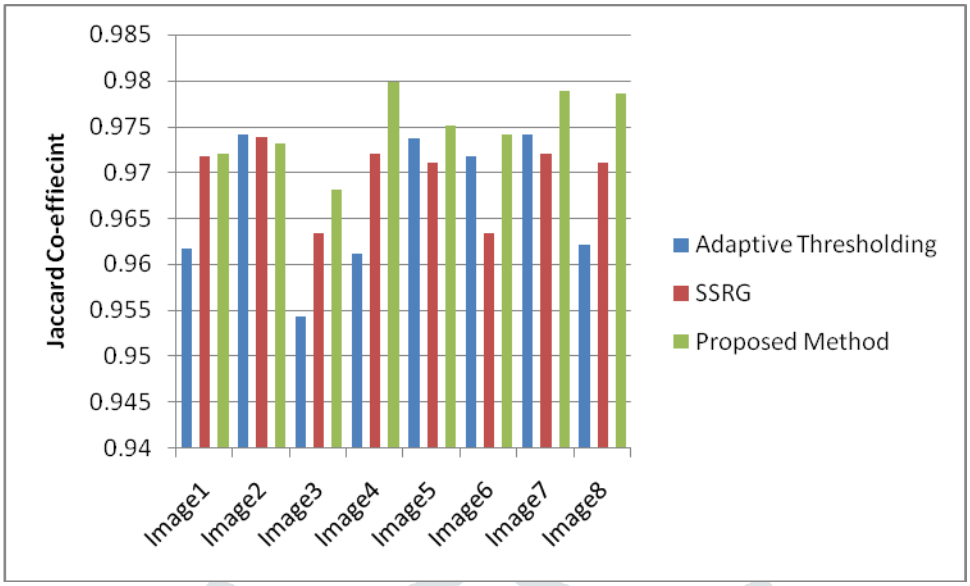

Fig 6. Jaccard Co-efficient bar chart

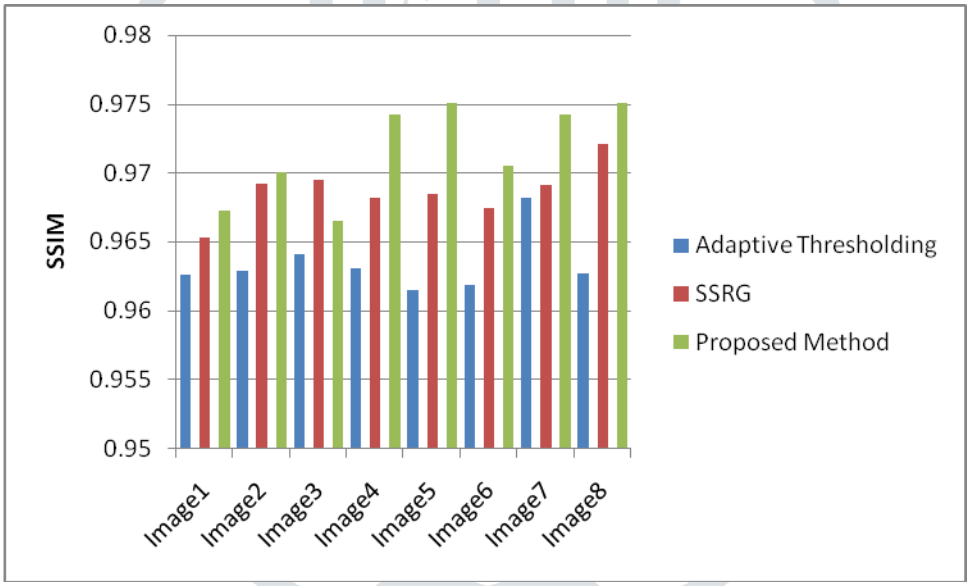

Fig 7. SSIM value bar chart

5. Conclusion

In this paper Region growing based on SUSAN principle is presented. This seed point selection method can detect the region in different intensity in the image automatically through self-adjust thresholds, which are computed based on the local gray discreteness of the pixel. The research work carried out the by Susan interest point detector and seeded Region Growing produce a new image segmentation result. Proposed algorithm in this work helps to find the best location for the seed points and best region from intensity based region optimization. A comparative experiment demonstrates that the proposed improved method has better performance in corner detection than traditional method.

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