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Quality Evaluation for Edge Detection of Chromosome G-band Images for Segmentation

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Abstract

Edge detection of chromosome in G-band type image is an important preprocessing step in segmentation. A chromosome type G-band image is generally very noise and poor image quality, lack of contrast and hold in image. A lot of edge caused by chromosome can easily mislead the edge detection algorithm. Particularly, the chromosome overlapping and touching, then it is very difficult to get a clear edge of the femur head. These extraneous edge and noise make edge detection very difficult and challenging, which is not well solved. This paper presents analysis of evaluation chromosome G-band image edge detection. It has been appeared in literature that there are 4 different techniques, i.e. Canny, Laplacain, Robert's, and Sobel, on chromosome image type G-band. From our study, we found that Robert's give promising results in edge detection. A success rate of 97.69% has been achieved.

Keywords: Edge Detection; Chromosome; Chromosome Analysis; Karyotype.

Introduction

Human chromosomes contain important information for cytogenetic analysis. Cytogenetic compares their patient's chromosome images against the prototype human chromosome band patterns. Chromosome images were acquired by microscopic imaging of metaphase or prophase cells on specimen slides. Karyotype analysis is a widespread procedure in cytogenetic to assess the possible presence of genetic defects, which is a useful tool for detecting deviation from normal cell structure. Abnormal cells consist of an excess or deficiency of a chromosome and structural defects. Nowadays, chromosome analysis and karyotyping analysis are performed manually in most cytogenetic laboratories. However, that process uses the time consuming, expensive procedure.

The current system for automatic chromosomes classification uses the image of edge is a fundamental feature. Edge is cause by changes in some physical properties of surfaces of the image. Most of research on image edge feature is always focusing on the detection and extraction method. The goal of edge detection is to recover the information about shapes and reflectance, or transmittance in images [1].

Cheng et al. [2] applied the canny edge detection method for medical image segmentation.

Heydarian et al. [3] proposed a novel method to detecting object edge in MR and CT images, which this method is applying an edge detection method based on the canny algorithm. Mondal et al. [4] applied the canny edge detection algorithm to detect edge information from the cephalograms images. Yo and Acton [5] proposed an automatic edge detection in ultrasound imagery based on normalized gradient and Laplacian operators. AI-Kofahi et al. [6] proposed an automatic detection and segmentation of cell nuclei in histopathology images which use a novel method combining multiscale Laplacian-of-Gaussian filtering constrained by distance-map-based adaptive scale selection for the nuclear seed points detection. Florea et al. [7] proposed an automatic contour detection for cellular images which use the Laplacian edge detector techniques. Brummer [8] presented the automatic detection of the longitudinal fissure in tomographic scans of the brain, which is use the sobel magnitude edge detection. Chi et al. [9] proposed preprocessing method for the CT images based on edge detection and spline fitting which use the sobel method to detect edge of procedure. Liu et al.[10] proposed the method of a nucleus segmentation in the context of Anti-Nuclear Antibodies (ANA) of diffused images which use the sobel edge detection to calculate the edge gradient of the object. Ruxin et al. [11] proposed a new method for medical image segmentation which use the Robert method to compensate the deficiency in edge detection. Zhang et al.[12] applied the contour detection for medical images of knee joint which use the Roberts Cross method in to the procedure of contour detection. Dawood et al. [13] proposed an automatic boundary detection of wall motion in two-dimensional echocardiography images which use the roberts operator in to edge detection to identify the wall boundaries.

Edge detection is one of the important contents of image processing, which is step of images segmentation, target area identification, and shape features extraction. In this paper, an attempt has been made to explore the best possible edge detection especially for chromosome G-band image. Performance comparison is carried out between the frequently use edge detection methods, including the classical Canny [14], Laplacian [12], Roberts [15] and Sobel methods [15]. Finally, the relative performance is examine on using the segmentation by OOB algorithm [16] on chromosome G-band image.

Material and Method

Object edges are the local characteristics of the image in the form of discontinuity, such as the mutation of the gray value, the mutation color, texture, structure, mutation and etc., while the edge of the object is the boundary between different regions. The picture edge has two characteristics which are the direction and the scope. Usually, gray scale of along-side edge is flat, and gray pixels scale of perpendicular-edge is thick [17].

Laplacian Differential Operator

Laplacian operator is defined as:

$$\nabla^2 f(x,y) = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2} \tag{1}$$

The difference form of which is

$$\nabla^2 f(x,y) = f(x+1,y) + f(x-1,y) + f(x,y+1) + f(x,y-1) - 4f(x,y) \tag{2}$$

The form below expressed template is,

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}, \text{Also used as} \begin{bmatrix} 1 & 1 & 0 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix}.$$

Laplacian operator is an isotropic operator, it is more appropriate in only care about the edge position without considering its surrounding pixel difference. Laplacian operator responds to isolate pixel more intense than to the edge or line, so it is only applied to the images without noise.

In existed noise circumstance, it is needed low-pass filter before using above operator[18].

Canny Operator

The Canny Edge Detector is one of the most commonly used image processing tools, detecting edges in a very robust manner. The Canny is used in the edge detection has four steps as follow: firstly, smooth image is using gauss filter; secondly, calculated gradient amplitude and direction is using the first-order finite difference; thirdly, Non-Maximum suppression is used with the image which scanned along the image gradient direction; finally, edge detects and connects in double thresholds algorithm.

The mathematical specific description

(1). 2-D Gaussian function is:

$$G(x,y)=\frac{1}{2\pi\delta^2}\exp\left(-\frac{(x^2+y^2)}{2\delta^2}\right) \tag{3}$$

In some direction *n*, first-order directional derivative *G*(*x,y*) is :

$$G_n=\frac{\partial G}{\partial n}=n\nabla G \tag{4}$$

$$n=\begin{bmatrix}\cos\theta & \sin\theta\end{bmatrix}^T,\nabla G=\begin{bmatrix}\partial G/\partial x & \partial G/\partial y\end{bmatrix}^T$$

where *n* is directional vector, ∇G is gradient vector. Let image *f*(*x,y*) convolutes with G_n , and simultaneously changes the direction of *n*, then *n* is orthogonal to the direction of testing edge when $f(x,y)*G_n$ obtains the maximum.

(2) Strength and the direction of edge

$$E_x=\partial G/\partial x * f(x,y) \tag{5}$$

$$E_y=\partial G/\partial y * f(x,y) \tag{6}$$

$$A(x,y)=\sqrt{E_X^2+E_Y^2} \tag{7}$$

$$\theta=\arctan(E_X/E_Y) \tag{8}$$

A(*x,y*) reflects the edge strength of points (*x,y*) on image, θ is an normal vector of point (*x,y*) in image.

(3) Just get global gradient is not enough to determine the edge, so for sure, must keep local maximal gradient points, and suppress the Non-Maximum.

(4) Typical method to reduce false edge number is to use a threshold. All values will be zero lower than the threshold. Double threshold value method will connect the edge into contour in G2(x,y). Therefore, when they get to the end of the contour, this algorithm will search the edge in eight adjacent point of G1(x,y), which can be connected to the contour. So, this algorithm collects the edge unceasingly in *G1*(*x,y*), until connected *G1*(*x,y*) so far [14,18].

Robert's Cross Operator

The Robert's cross operator [15] performs a simple, quick to computes, 2-D spatial measurement on an image. It thus highlights regions of high spatial frequency which often corresponds to edge. Pixel values at each point in the output represent the estimated absolute magnitude of the spatial gradient of the input image at that point. In theory the operator consists of pair of 2×2 convolution kernels as shown below. One kernel is simply the other rotated by 90°.

$$G_y=\begin{bmatrix}+1 & 0\\ 0 & -1\end{bmatrix}\qquad G_y=\begin{bmatrix}0 & +1\\ -1 & 0\end{bmatrix} \tag{9}$$

These kernels are designed to respond maximally to edges running at 45^0 to the pixel grid, one kernel for each of the two perpendicular orientations. The edge gradient magnitude is given by,

$$|G| = \sqrt{G_X^2 + G_Y^2} \cong |G_X| + |G_Y| \tag{10}$$

The angle of orientation of the edge giving rise to the spatial gradient is given by,

$$\theta = \arctan(\frac{G_X}{G_Y}) - \frac{3\pi}{4} \tag{11}$$

Sobel Operator

The Sobel operator [15] performs a 2-D spatial gradient measurement on an image and typically it is used to find the approximate absolute gradient magnitude at each point in an input image. In theory the operator consists of a pair of 3×3 convolution kernel as shown below.

$$G_X = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad G_Y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{12}$$

These kernels are designed to most effectively to edges running, both vertically and horizontally, relative to the pixel grid. Each kernel is for each perpendicular orientation. The edge gradient magnitude is give by,

$$|G| = \sqrt{G_X^2 + G_Y^2} \cong |G_X| + |G_Y| \tag{13}$$

The angle of orientation of the edge giving rise to the spatial gradient is give by,

$$\theta = \arctan(\frac{G_X}{G_Y}) \tag{14}$$

System Summary

Figure 1 illustrates the flowchart of the proposed chromosome edge detection evaluation system. The procedures in this work consist of three steps: preprocessing, edge detection, and segmentation. In the first step, we applied the Histogram equalization[19] and the Otsu's[20] for preprocessing chromosome images. Secondly, the other method of edge detection was applied to edge detect the chromosome images. In the last step, we adopted the oriented bounding boxes (OBBs) [16], which used to chromosomes segmentation from background, and the result can be counted and confirmed by an expert. The details of each step are described in the following.

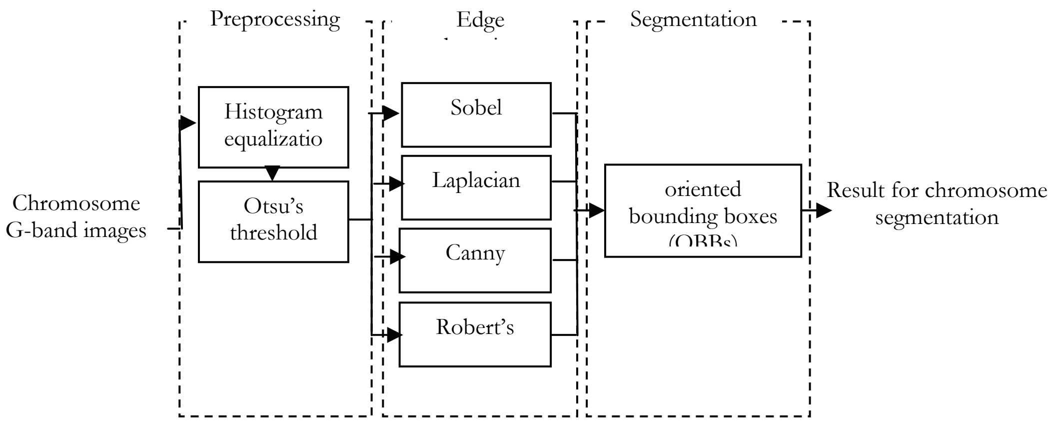


Figure 1. Flowchart for evaluate system of chromosome edge detection

Data set

The proposed system has been tested with a database consist of 917 chromosomes from 30 cells, 16 of which are male and 14 female provided by the Center of Medical Genetics Research Rajanukul Institutes of Health. These 30 cells consist of 13 cells with 46 chromosomes, 15 cells with 45 chromosomes and 2 cells with 47 chromosomes. There are 13 cells with 46 chromosomes having strange constellations. The set of cells with one extra chromosome is composed of 13 Down, 12 Edwards and Pätau syndromes, one trisomy 15, three trisomy 16 and one trisomy 10.

Performance Study

Experiments are performed on a PC with Intel (R) Core (TM) 3.30 GHz CPU and 2 G main memory, running on Windows 7 .The program are implemented by Opencv 2.1 library for Microsoft visual C++.

The performance of the chromosome segmentation step is evaluated using the overall and chromosomes segmentation accuracy [21], defined as

$$Accuracy = \frac{Chromosome\_segmentation}{Overall\_segmentation} x100 \tag{15}$$

The proposed method was compared with four traditional methods; Canny, Laplacian, Roberts and Sobel methods. 30 chromosome spread images are test in our experiment. Figure 2 shows the results comparing between the four methods for edge detection on chromosome cells.

Figure 3 shows that the comparison method gives the highest performance of chromosome segmentation, and the image demonstrates many effects such as contrast and none stable of chromosome distribute.

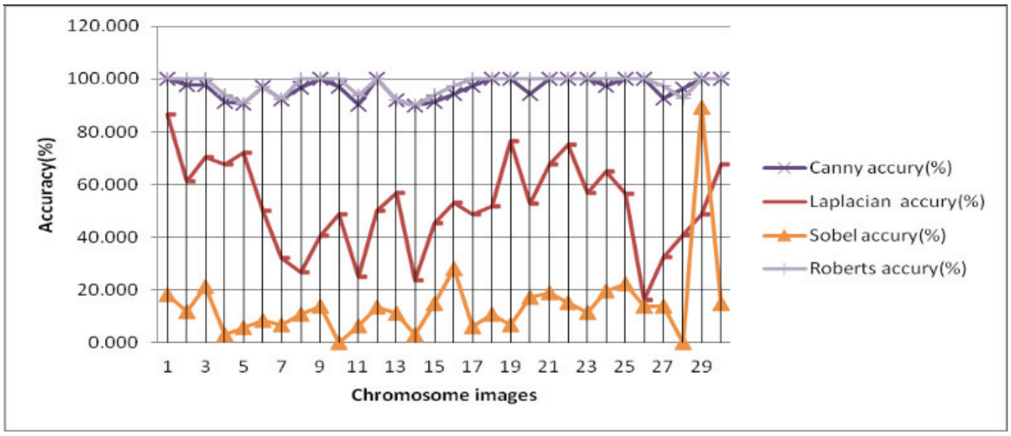
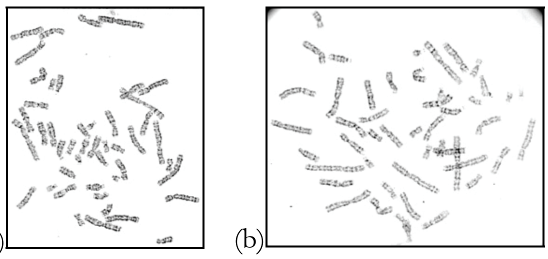


Figure 3. The results of chromosome segmentation by Canny, Laplacia, Robert's, and Sobel

In all methods, the chromosome image number 29 has high accuracy because it has highest contrast and highest stability of chromosome distribution as shown in figure 4(a). The image number 14 is low accurate because it has lowest contrast and has no stability of chromosome distribution as shown in figure 4(b).



(a) (b)

Figure 4. (a) Show the original image no. 29. **(b)** Show original image no. 14.

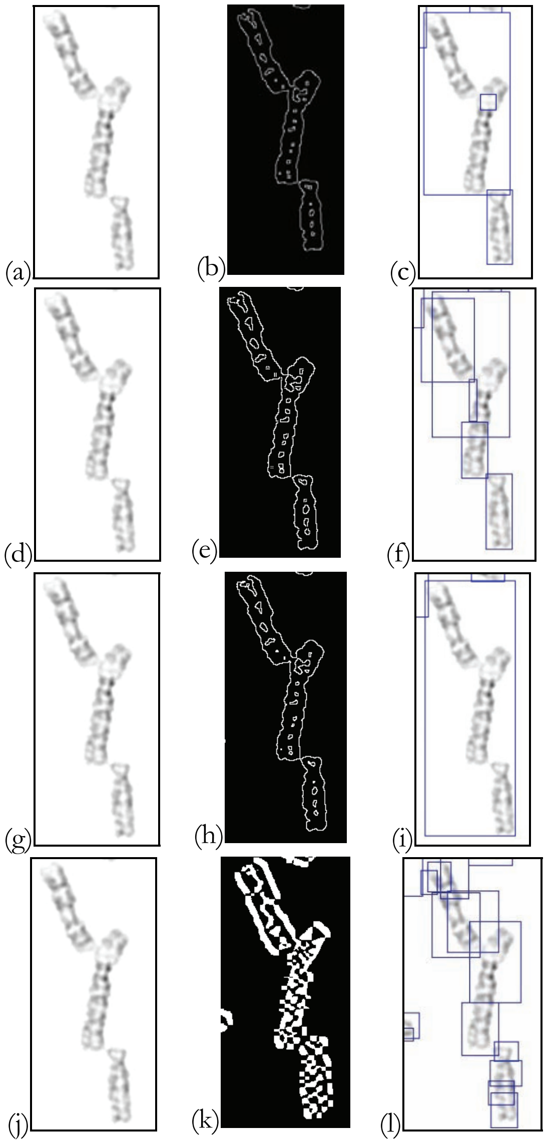


Figure 2. Original images **(a)**, **(d)**, **(g)**, and **(j)** and some test image **(b)** Canny, **(e)** Laplacian, **(h)** Rebth's, and **(k)** Sobel theirs results of OBB **(c)**, **(f)**, **(i)**, and **(l)**

The average of accuracy chromosome segmentation values are shown is Table 1.

Table 1. The comparisons of accuracy for segmentation

Method	Accuracy (%)
Canny	96.54
Laplacian	51.2
Sobel	14.53
Robert's	97.69

The edge detection performance for the Canny, Laplacian, Robert's, and Sobel are listed in Table 1. From this result, it can easily see that, the Robert's method obtains the most accuracy. The average accuracy rate of segmentation of the Robert's method is 97.69%.

However, in this article we care more for the accuracy of the chromosome edge detection which can be for a further process on improve chromosome edge detection. The method can be successfully applied for edge detection of boundaries of chromosome image model, specifically as described above for chromosome G-band images. However, we believe that it can be easily applied to several other applications not only chromosome G-band images but generally computer graphics.

Conclusions

The results of our study indicate that the Robert's method obtains the highest accuracy compared with the other three algorithms. The average accuracy rate of segmentation of the Robert's method is 97.69%, which is very close to Canny's method of 96.54%. In addition, the characteristic of chromosome has effects of edge detection such as the contrast in the images and stable of chromosome distribute. Therefore the preprocessing method is needed in first step of procedure automatic edge detection. Here we suggest completed package for chromosome edge detection.

Conflict of Interest

The authors declare that they have no conflict of interest.

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