A Hybrid Edge Detection Method for Cell Images Based on Fuzzy Entropy and the Canny Operator

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***Abstract*—Since cell biologists need to use image processing techniques, such as edge detection, to analyze cell images the precision of these techniques is pivotal to their work. Due to the often low quality of cell images, existing edge detectors fail to routinely produce highly accurate results. In this paper, a novel hybrid method based on the canny operator and fuzzy entropy theory is proposed. The method calculates the fuzzy entropy of gradients from an image to decide the threshold for the canny operator. Application of the method to cell images has demonstrated its excellent performance in edge detection and robustness in the presence of noise.**

***Index Terms*—cell images, canny operator, fuzzy entropy theory, hybrid method, image processing**

I. Introduction

Numerous image processing techniques have been applied to images of cells in order to assist cell biologists in their research. Since it is an essential step prior to subsequent analyses [1] the performance of the method used for cell segmentation is of particular importance. However, the conditions for capturing cell images vary widely that often means that: the contrast is extremely low; the distribution of gray scale is non-uniform; and the images are noisy (e.g. with salt and pepper noise). These factors increase the difficulty of performing accurate detection. Although there are a great deal of existing segmentation methods [2]-[4], few of them can simultaneously solve these three problems.

Edge detection is a widely employed technique for image segmentation, based on the assumption that the image gradient changes sharply near the cells' borders. Most techniques (e.g Sobel, Roberts, and Prewitt) use a differentiation filter in order to approximate the first-order image gradient [5]. Letting *f(x, y)* be a raw image then the first-order gradient is defined as follows:

$$\nabla f(x,y) = [G_x, G_y]^T = \left[\frac{\partial f}{\partial x}\frac{\partial f}{\partial y}\right]^T \tag{1}$$

Following the generation of a gradient map, potential edges are extracted by thresholding the gradient. Based upon this approach modified methods such as the Laplacian of Gaussian operator (LoG) have been established that uses the second-order image derivative, also named as Laplacian magnitude, to extract edges. The Laplacian magnitude is defined by:

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

However, the LoG operator is very sensitive to noise, a problem addressed by the development of methods to remove false edges [6], [7].

In 1986 Canny proposed method that has achieved widespread use that first applies Gaussian derivatives to the image, before isolating candidate edge by non-maximum suppression and extracting them via hysteresis thresholding [8]. A method to extract edges missed by the Canny detector was later suggested by Ding [9]. In more recent work Elder and Zucker [10] introduced a method to determine edges at a multitude of scales, whilst an adaptive smoothing method has also been proposed [11].

Among these methods the Canny operator is one of the most powerful edge detectors with proven success when applied to various tasks. However, due to the often low quality of cell images, its performance is lower than would be expected. In this paper, a novel method to improve the performance of the Canny edge detector when applied to cell images, is proposed. The thresholding method based on Fuzzy Entropy theory is used with the Canny operator to appropriately select the threshold gradient. Essentially this approach takes more information into consideration when performing the thresholding that results in a greater robustness to noise.

II. Algorithm

In this section, the ways to address the problems outlined in the Introduction are given.

A. Low Contrast

The quality of cell images generated by biological microscopes is often less than ideal in terms of the cells'

Manuscript received July 10, 2014; revised November 20, 2014.

doi: 10.12720/joig.2.2.135-139

contrast and sharpness (i.e. the cells are blurred). This leads to a loss of detail and detection of false edges.

An existing approach for image quality enhancement [12] is implemented in the proposed method. It uses morphological transforms, top-hat and bottom hat, to extract the bright field and dark field in the image. Let *f* be a grayscale image; and *b(x)* be a grayscale structuring element. The top-hat and bottom-hat transforms are represented as follows,

$$T_{top-hat} = f - f \circ b \tag{3}$$

where $\circ$ denotes the opening operation.

$$T_{bottom-hat} = f \bullet b - f \tag{4}$$

And $\bullet$ is the closing operation.

To increase contrast, the proposed approach processes these two fields back to the original image via:

$$f_{enhanced} = f + \frac{T_{top-hat}}{2} - \frac{T_{bottom-hat}}{2} \tag{5}$$

Although this method enhances image contrast it introduces the problem that as image quality is enhanced so the noise in the image is increased.

B. Non-Uniform Gray Scale Distribution

The traditional Canny edge detector is a global operator using the same parameters, such as the threshold applied to gradients, to process the whole image. This leads to problems when the image has a non-uniform distribution of gray scales. In such images, the appropriate threshold varies across the image and should be adjusted from a global to local values to accommodate fluctuations of gray levels.

To introduce local thresholding the image is split into sub-images with each sub-image then processed with a revised Canny operator. The final output image is produced by assembling results from these sub-images. By allowing the use of different parameters to be applied to different areas of the image the inhomogeneity problem is solved.

C. Noise

A typical Canny operator uses the following steps to extract edges:

- Remove white Gaussian noise by smoothing the image with a Gaussian filter.
- Calculate the magnitude and direction of the gradient at each pixel.
- If the gradient's magnitude at the processing point is larger than the two neighbours' gradients, when laid in the gradient direction, the processing pixel is marked as the edge. Otherwise, it is marked as the background.
- Use hysteresis thresholding to remove weak edges.

Applying this approach to real data suggests that inaccuracies in segmentation result primarily from Step 3 since it is a process that is very sensitive to noise. This is the reason why an alternative method is proposed that is based on Fuzzy Entropy, whose basic theory is now introduced.

D. Fuzzy Entropy

Fuzzy entropy is the entropy of a fuzzy set, loosely representing the information of uncertainty [13], [14]. It is usually used to quantify the value of information included in a message. Defining *X* as a set of discrete random variable with values $\{x_1, ..., x_n\}$ and *P(X)* as the probability mass function then the corresponding entropy *H* is defined as:

$$H(X) = \sum_i P(x_i) I(x_i) = -\sum_i P(x_i) \log_b P(x_i) \tag{6}$$

where *I* is the information content of *X*, and *b* is the base of the logarithm.

The thresholding method based on Fuzzy Entropy theory calculates the entropy of a fuzzy set and then normalizes it, which maximizes the entropy, as the threshold. Fuzzy sets were first defined by Zadeh in 1965 [15] and are sets whose elements have degrees of membership. The pixels in an image can be seen as an example of fuzzy sets. In an image, there are usually two classes, objects and background. If a membership function is defined, the degrees of pixels belonging to the different sets can be calculated. Based on the obtained memberships, pixels can be separated into correct groups; the basic idea behind pixel clustering.

In the proposed method, the Fuzzy Entropy theory is used to distinguish gradients for edges from ones produced by noise. The gradients of the image generated by the Canny operator is a set of values which can be classified into two groups, edges and noise. Here the membership functions, μ, are defined by:

$$\mu_A(x) = \begin{cases} 0, & x \in B \\ \dfrac{b-x}{b-a}, & x \in A \cap B \\ 1, & x \in A \end{cases} \tag{7}$$

$$\mu_B(x) = \begin{cases} 1, & x \in B \\ \dfrac{x-a}{b-a}, & x \in A \cap B \\ 0, & x \in A \end{cases} \tag{8}$$

The relationship between membership functions is shown diagrammatically in Fig. 1.

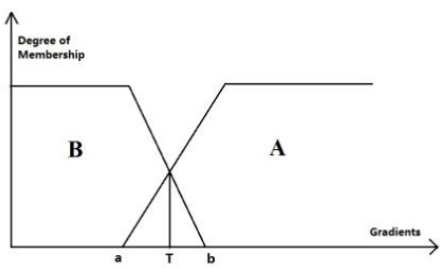

Figure 1. Diagram of membership function

The parameters, a and b, are unknown, which means the entropies of these two groups change in response to alterations in a and b. Theoretically, a larger entropy

means that the test objects contain more information. Therefore, the gradient maximizing the joint entropy of this fuzzy set is set as the threshold. The concept of joint entropy was introduced in [16]. Let the entropy be H, so that the entropy for A can be represented as,

$$H(A) = -\sum_{j=1}^{L} \frac{\mu_A(j)h_j}{P(A)} \lg \frac{\mu_A(j)h_j}{P(A)} \tag{9}$$

where $h(j) = \frac{N_j}{N_{total}}$; N_j is the number of points whose gradients equal to j; and N_{total} denotes the number of total points.

Hence, the joint entropy is,

$$\begin{aligned} H(AB) &= H(A|B) + H(B) \\ &\le H(A) + H(B) \end{aligned} \tag{10}$$

They become equivalent if and only if these two sets of data are independent. From (10), it is obvious that the task of thresholding is converted to that of finding the maximum of the total entropy of gradients.

III. Results and Analyses

Images were processed to compare the results from the revised Canny operator with those produced using typical edge detectors. As introduced in the previous section, the edges in cell images are usually blurred and so details are often lost during the segmentation process. An example is shown in Fig. 2.

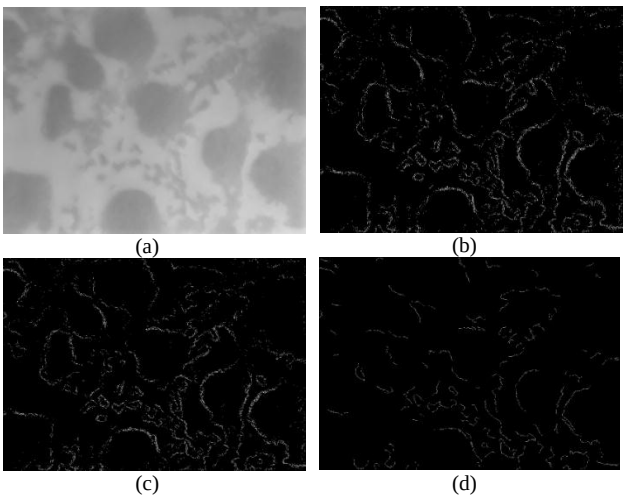

Figure 2. (a) Original image; (b) Result from Sobel; (c) Result from Prewitt; (d) Result from typical Canny

The low image contrast is the main reason for the loss of edges with the Canny approach suffering more than the others. Hence, the cell image is first enhanced to make the edges sharp and clear before further processing, although this is at the cost of quality improvement, with the noise increased.

As shown in Fig. 3 this not only produces more details, but also more noise. The problem changes from one of low contrast to that of increased noise; so a noise insensitive edge detection method is required.

The revised Canny divides the image into se sub-images that are individually processed in order to reduce the impact of the inhomogeneous distribution of gray scales. After image separation, the method firstly calculates the histogram of gradient (HoG) of the processing sub-image as shown in Fig. 4 where the x-axis represents the values of gradients and the y-axis is the number of points with each value of gradient.

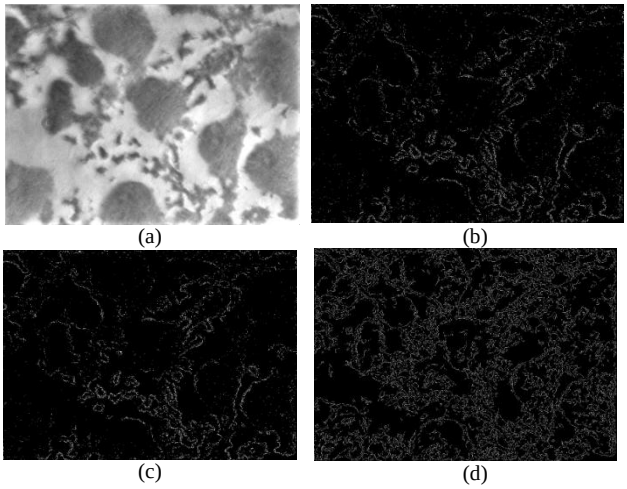

Figure 3. (a) Enhanced image; (b) Result from Sobel; (c) Result from Prewitt; (d) Result from typical Canny

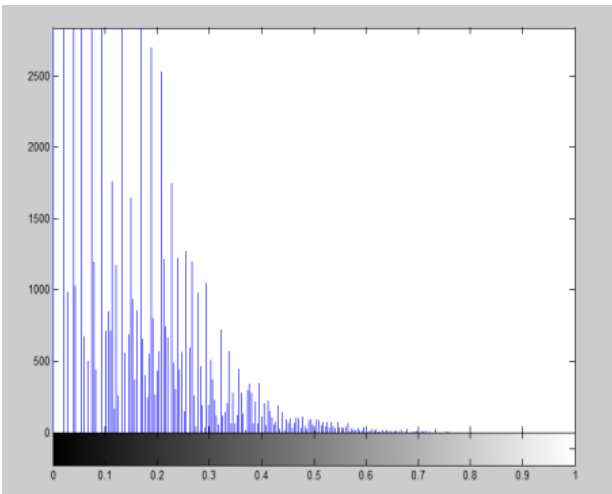

Figure 4. Histogram of gradients

The edges, which have high gradients, only occupy a small proportion of points in the image. Conversely, the points in the objects and background, along with those generated by noise, usually have a relatively lower gradient. The problem is to find a value that ideally partitions the points in the HoG into correct classes, which is achieved using the theory of Fuzzy Entropy.

Using this approach the modified Canny operator is more robust in the presence of noise. The detector was applied to the cell images and outcomes compared to those produced by benchmarking algorithms, which are shown in Fig. 5.

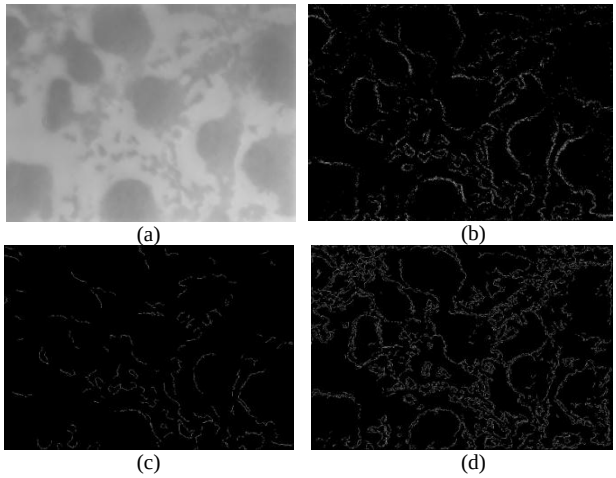

Figure 5. (a) Original image; (b) Result from Prewitt; (c) Result from typical Canny; (d) Result from the revised Canny

Due to the low quality of the cell images, there are unexpected problems in the results from the benchmarking methods. In the results produced using the typical Canny, many detailed edges are missed. Although the Prewitt operator is better, many false edge points occur around the edge lines and most of the main boundaries are not detected. These problems will definitely lead to difficulties in performing subsequent image analyses.

The proposed method successfully deals with these problems. Even though the signal-to-noise ratio in the image is high, a problem increased even further after image enhancement, the revised Canny edge detector still has an excellent segmentation performance so retaining much of the detailed information. It overcomes the three issues, of: low contrast, non-uniform gray scale distribution, and noises.

IV. Application

The implementation time of the proposed method is fast enough for real-time applications demonstrated by the processing of video data illustrated in Fig. 6.

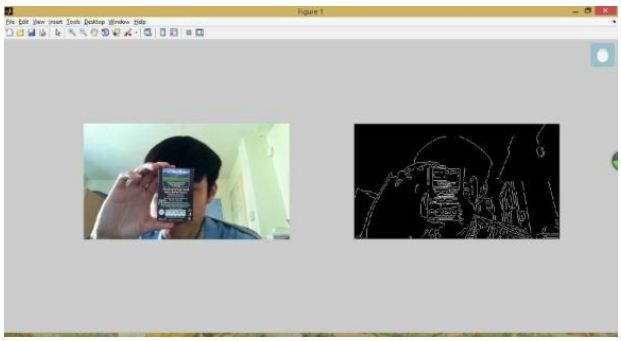

Figure 6. Real-time system

Although, due to the unstable light conditions, some errors occur and some details are lost, generally the results are acceptable and the system is capable of operating in real-time. Since the light conditions are relatively steady in a microscope it is expected that the system will offer better performance that current processing methodologies and can be implemented to process real-time cell images.

V. Conclusion

An edge detector suitable for cell images based on the Canny operator and the Fuzzy Entropy theory has been introduced. Due to the routine problem of low contrast in cell images, the method first enhances cells' image quality by morphological operations. However this process introduces noise into the image and so requires use of a robust edge detector.

Widely used existing edge detection methods were tested and shortcomings of benchmarking methods found. For example, most of them are sensitive to noise and unable to deal with inhomogeneous gray scale distribution problem.

Among the existing detectors, the Canny operator was selected as a method with high potential. Therefore it was revised to use Fuzzy Entropy theory to improve its performance in the presence of noise. Since the entropy is a measurement of the volume of information contained in a message, the larger the entropy then the more detailed the information that remains. So the gradient maximizing is achieved using fuzzy entropy to provide the threshold for the Canny operator.

Through comparisons between the proposed method and others, such as Prewitt and typical Canny operator, it has been shown that the revised Canny edge detector has better robustness to noise and achieves better performances in detail recognition. Undoubtedly, it is a more suitable method for edge detection in cell images and so has the potential to be of value to cell biologists.

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