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Color Cell Image Segmentation Based on Chan-Vese Model for Vector-Valued Images

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ABSTRACT

In this paper, we propose a color cell image segmentation method based on the modified Chan-Vese model for vector-valued images. In this method, both the cell nuclei and cytoplasm can be served simultaneously from the color cervical cell image. Color image could be regarded as vector-valued images because there are three channels, red, green and blue in color image. In the proposed color cell image segmentation method, to segment the cell nuclei and cytoplasm precisely in color cell image, we should use the coarse-fine segmentation which combined the auto dual-threshold method to separate the single cell connection region from the original image, and the modified C-V model for vector-valued images which use two independent level set functions to separate the cell nuclei and cytoplasm from the cell body. From the result we can see that by using the proposed method we can get the nuclei and cytoplasm region more accurately than traditional model.

Keywords: Cell Image; Color Image Segmentation; Level Set Method; Active Contour Model

1. Introduction

Worldwide, especially in middle and low income countries, cervical cancer is the second most common cancer in women, and the third most frequent cause of cancer death. But cervical cancer is more preventable than others because it has a very long time precancerous stage and can be easily detected by a routine screening test. So it is necessary to develop the automated cervical smear screening analysis system to assist the diagnosis of cervical cancer. The quantitative analysis and automatic recognition of cervical cell image contain the following three steps: cell image segmentation, features extraction and cell image recognition. Segmentation of cells in cytological image is the fundamental and key point of quantitative analysis and affects the classification result directly.

The early cervical cell image segmentation method was focused on the nuclear region segmentation [1-3]. After finding that the cytoplast region and the whole cell body have played important role in cervical cell image classification and diagnosis, some researchers employed several methods to segment the cell nucleus and cell cytoplasm [4-6]. Because the cervical smear images are frequently contaminated, the contrast between cell nucleus and cytoplasm is lower, which makes the contours of nuclei and cytoplasm very vague even for the abnormal cells. In addition, the cells shape, size and topological structure are strongly different from each other especially for the severe dysplastic cells. While the Chan-Vese (C-V) active contour model without edges, proposed in [7] has been used in gray cervical cell image segmentation perfectly in [8]. The modified C-V model can separate the cell nuclei and cytoplasm precisely. In reality the collected and processed cell images are all color images, so it's necessary to research the method of the color cell image segmentation. In this paper, we propose a color cell image segmentation method by using vector-valued C-V model.

2. Cell Image Processing

The cells in the cervical smear image are poorly contrasted and more kinds of cells are found in high degree of overlapping because of the diversity in the process of collection, smear staining or the affection of bleeding and inflammation. On the other hand, cells in different growth stages or variant lesion degrees have diverse size,

shape, morphology, color, texture and density. It's hard to use a global segmentation method to extract every connected cell region from the cervical smear image precisely. These features brought us to use coarse-to-fine segmentation strategy.

Before the cell coarse segmentation, we should do some pre-processing steps to select regions of interest (ROI) which contains the object cell. In each ROI, there is only one object of interest in each field. So the next fine segmentation can be implanted on the choosing object. In this paper we use auto dual-threshold segmentation as the coarse segmentation method [8]. As there are three components in cervical cell image: cell nucleus, cell cytoplasm and background, we just need to segregate the nucleus and cytoplasm from the background domain, which means that two thresholds will be used in the algorithm.

Combine cell nucleus region with cytoplasm region of the result after auto-threshold segmentation and we can get a binary image. Morphological opening operation, which consists of an erosion operation followed by a dilation operation, has been used to eliminate the small isolated noise and void area. After the mathematical morphology opening operation, isolated noise and hole smaller than structure element will be eliminated. Scanning the binary image after the processing mentioned above again and labeling it by 8 neighborhoods searching algorithm, we can segregate the minimum enclosing rectangle of the connected region by its serial number. Expand the rectangle to x pixels in up and down directions and y pixels in left and right directions, the region after expanding is deemed as the region of interest where the fine segmentation will be operated on it.

3. Gray Cell Image Segmentation

Chan-Vese model (C-V model) proposed by T. F. Chan and L. A. Vese is a classical level set based active contour model [9-15]. The model is appropriate for segmenting the images containing the objects that have fuzzy or discontinuous borders and complicated topological structures. Here we use the modified C-V model to segment the gray scale cervical cell image [8].

Let $\Omega \in R^d$ be the image domain, Ω1, Ω2 and Ω3 represent the cell nucleus, cell cytoplasm and background regions respectively. In general case, the intensity of background is the highest among the three regions, the cell cytoplasm is in the second place, and the cell nucleus is the lowest. In addition the cell nucleus is always inside the cell nucleus. The structure of the cervical cell image shows in **Figure 1**.

In this section, we employ two independent level-set functions ϕ_1 and ϕ_2 to segment the cervical cell image, the contour curves C_1 and C_2 are represented by their zero level set functions.

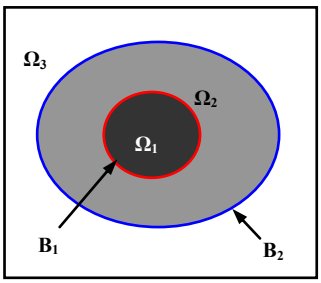

Figure 1. Structural representation of cervical cell image.

The level set functions and their regional classification show in **Figure 2**. The definition of the level set function is that if the point is inside the curve then $\phi > 0$, if the point is outside the curve the $\phi < 0$ and if the point is on the curve then $\phi = 0$. The energy functional of this model is defined as

$$E(c_1,c_2,\phi_1;d_1,d_2,\phi_2) = E_1(c_1,c_2,\phi_1) + E_2(d_1,d_2,\phi_2) \quad (1)$$

where $E_1(c_1,c_2,\phi_1)$ and $E_2(d_1,d_2,\phi_2)$ are the energy functional of level set functions ϕ_1 and ϕ_2 based on Chan-Vese model; c_1 and c_2 denote the mean of the image intensity inside and outside the contour curve C_1; d_1 and d_2 denote the mean of the image intensity inside and outside the contour curve C_2.

Assuming c_1, c_2, d_1 and d_2 are constants and minimizeing energy functional $E(c_1,c_2,\phi_1;d_1,d_2,\phi_2)$ with respect to level set functions ϕ_1 and ϕ_2 yield the evolving equations of the two level set functions:

$$\frac{\partial\phi_1}{\partial t} = \delta_\varepsilon(\phi_1)\left\{\mu_1 \operatorname{div}\left(\frac{\nabla\phi_1}{|\nabla\phi_1|}\right) + (1-\lambda_1)\cdot\left[-(u_0-c_1)^2 + (u_0-c_2)^2\right] + \lambda_1(c_2-c_1)\left(\frac{c_1-u_0}{A_{11}/A} + \frac{c_2-u_0}{A_{12}/A}\right) - \nu_1\right\} \quad (2)$$

$$\frac{\partial\phi_2}{\partial t} = \delta_\varepsilon(\phi_2)\left\{\mu_2 \operatorname{div}\left(\frac{\nabla\phi_2}{|\nabla\phi_2|}\right) + (1-\lambda_2)\cdot\left[-(u_0-d_1)^2 + (u_0-d_2)^2\right] + \lambda_2(d_2-d_1)\left(\frac{d_1-u_0}{A_{21}/A} + \frac{d_2-u_0}{A_{22}/A}\right) - \nu_2\right\} \quad (3)$$

where A is the area of the image, A_{11} and A_{12} are the area inside and outside the contour curve C_1, A_{21} and A_{22} are the area inside and outside the contour curve C_2, λ_1 and λ_2 are adjustable weight values used in level set evolving functions.

$$A_{11} = \iint_\Omega H(\phi_1)\mathrm{d}x\mathrm{d}y,\quad A_{12} = \iint_\Omega [1-H(\phi_1)]\mathrm{d}x\mathrm{d}y$$
$$A_{21} = \iint_\Omega H(\phi_2)\mathrm{d}x\mathrm{d}y,\quad A_{22} = \iint_\Omega [1-H(\phi_2)]\mathrm{d}x\mathrm{d}y$$
$$A = A_{11} + A_{12} = A_{21} + A_{22} \quad (4)$$

For cervical cell image, the intensity differences between cell nucleus or cell cytoplasm and the background

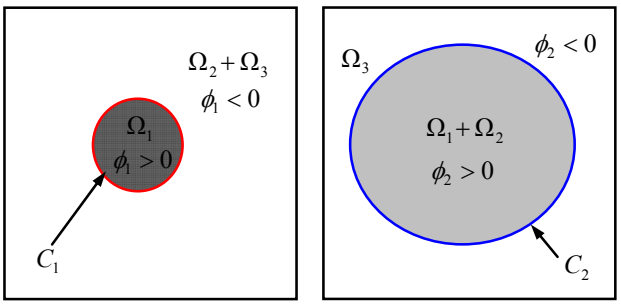

Figure 2. Level set functions and regional division: (a) Level set function ϕ_1 and relevant regional classification, (b) Level set function ϕ_2 and relevant regional classification.

are much bigger than the intensity difference between cell nucleus and cell cytoplasm. Let h_1, h_2 and h_3 represent the mean of the image intensity within cell nucleus, cell cytoplasm and background, then $h_3 > h_2 > h_1$. Associating with the definition mentioned above we can obtain the expression that $d_2 = h_3 > c_2 > h_2 > d_1 > c_1 = h_1$, in addition we do fine segmentation in ROI, so the area of background A_{22} is small relatively. So the right side of the Equation (3) is huge, considering the stabilization of the algorithm, let $P_{21} = \dfrac{A}{A_{22}}$ and $P_{22} = \dfrac{A}{A_{21}}$, we can rewrite the Equation (3) to the following equation.

$$\begin{aligned}\frac{\partial\phi_2}{\partial t} = \delta_\varepsilon(\phi_2)\Bigg\{&\mu_2\,\mathrm{div}\left(\frac{\nabla\phi_2}{|\nabla\phi_2|}\right)+(1-\lambda_2)\\ &\cdot\left[-(u_0-d_1)^2+(u_0-d_2)^2\right]\\ &-\lambda_2(d_2-d_1)\left[u_0-(d_1P_{22}-d_2P_{21})\right]-\nu_2\Bigg\}\end{aligned} \tag{5}$$

Similarly for the fixed level set functions ϕ_1 and ϕ_2 minimizing the energy functional $E(c_1,c_2,\phi_1;d_1,d_2,\phi_2)$ with respect to c_1, c_2, d_1 and d_2, we can get the following equations:

$$c_1 = \frac{\int_\Omega u_0 H(\phi_1)\,\mathrm{d}x\mathrm{d}y}{\int_\Omega H(\phi_1)\,\mathrm{d}x\mathrm{d}y},\quad c_2 = \frac{\int_\Omega u_0\left[1-H(\phi_1)\right]\mathrm{d}x\mathrm{d}y}{\int_\Omega\left[1-H(\phi_1)\right]\mathrm{d}x\mathrm{d}y} \tag{6}$$

$$d_1 = \frac{\int_\Omega u_0 H(\phi_2)\,\mathrm{d}x\mathrm{d}y}{\int_\Omega H(\phi_2)\,\mathrm{d}x\mathrm{d}y},\quad d_2 = \frac{\int_\Omega u_0\left[1-H(\phi_2)\right]\mathrm{d}x\mathrm{d}y}{\int_\Omega\left[1-H(\phi_2)\right]\mathrm{d}x\mathrm{d}y} \tag{7}$$

Generally the updating of the level set functions and the computation of c_1, c_2, d_1 and d_2 are processing alternatively until the solution is stationary. When the evolving process has finished, the contour curves corresponding to the zero level set functions of ϕ_1 and ϕ_2 are the boundaries of the segmented domain. The contour curve represented by zero-level set of ϕ_1 is entitled cell nucleus contour curve, and the contour curve represented by zero-level set of ϕ_2 is called cell body contour curve, they are combined and defined as cell contour curve.

4. Color Cell Image Segmentation

Now we put the previous modified C-V model of the cell image segmentation method to the vector case [12]. There are 3 channels in color cell image, red, green and blue. Let $u_{0,i}$ be the ith channel of an image on Ω, while i=1,2,3 represent the red, green and blue channel respectively. Let $c^+ = (c_1^+,\cdots,c_3^+)$, $c^- = (c_1^-,\cdots,c_3^-)$, $d^+ = (d_1^+,\cdots,d_3^+)$ and $d^- = (d_1^-,\cdots,d_3^-)$ be four unknown constant vectors. The extension of the C-V model to the color cell image segmentation model in vector case is

$$E(c^+,c^-,\phi_1;d^+,d^-,\phi_2) = E_1(c^+,c^-,\phi_1)+E_2(d^+,d^-,\phi_2) \tag{8}$$

According to the previous description of gray cell image segmentation and Equations (2) and (5), assuming c^+, c^-, d^+ and d^- are constant vectors and minimizing $E(c^+,c^-,\phi_1;d^+,d^-,\phi_2)$ with respect to ϕ_1 and ϕ_2, we can get the following equations:

$$\begin{aligned}\frac{\partial\phi_1}{\partial t} = \delta_\varepsilon(\phi_1)\Bigg\{&\mu_1\,\mathrm{div}\left(\frac{\nabla\phi_1}{|\nabla\phi_1|}\right)+\frac{1}{3}\sum_{i=1}^{3}(1-\lambda_{1,i})\\ &\cdot\left[-(u_{0,i}-c_i^+)^2+(u_{0,i}-c_i^-)^2\right]\\ &+\frac{1}{3}\sum_{i=1}^{3}\lambda_{1,i}(c_i^- - c_i^+)\frac{u_{0,i}-(c_i^+P_{12}+c_i^-P_{11})}{P_{11}P_{12}}-\nu_1\Bigg\}\end{aligned} \tag{9}$$

$$\begin{aligned}\frac{\partial\phi_2}{\partial t} = \delta_\varepsilon(\phi_2)\Bigg\{&\mu_2\,\mathrm{div}\left(\frac{\nabla\phi_2}{|\nabla\phi_2|}\right)+\frac{1}{3}\sum_{i=1}^{3}(1-\lambda_{2,i})\\ &\cdot\left[-(u_{0,i}-d_i^+)^2+(u_{0,i}-d_i^-)^2\right]\\ &+\frac{1}{3}\sum_{i=1}^{3}\lambda_{2,i}(d_i^- - d_i^+)\left[u_{0,i}-(d_i^+P_{22}-d_i^-P_{21})\right]-\nu_2\Bigg\}\end{aligned} \tag{10}$$

where $\mu_1 \geq 0$, $\mu_2 \geq 0$, $\nu_1 \geq 0$ and $\nu_2 \geq 0$ are the fixed weight of the vector-valued C-V model, $\lambda_{1,i} > 0$ and $\lambda_{2,i} > 0$ are the weight coefficients of each channel, and

$$A_{11} = \iint_\Omega H(\phi_1)\,\mathrm{d}x\mathrm{d}y,\quad A_{12} = \iint_\Omega\left[1-H(\phi_1)\right]\mathrm{d}x\mathrm{d}y$$

$$A_{21} = \iint_\Omega H(\phi_2)\,\mathrm{d}x\mathrm{d}y,\quad A_{22} = \iint_\Omega\left[1-H(\phi_2)\right]\mathrm{d}x\mathrm{d}y$$

$$P_{11} = \frac{A_{11}}{A},\quad P_{12} = \frac{A_{12}}{A},\quad P_{21} = \frac{A}{A_{22}},\quad P_{22} = \frac{A}{A_{21}}$$

$$A = A_{11}+A_{12} = A_{21}+A_{22} = \iint_\Omega \mathrm{d}x\mathrm{d}y$$

While minimizing the energy with respect to the constants c^+, c^-, d^+ and d^-, we can obtain

$$c_i^+ = \frac{\iint_\Omega u_{0,i}(x,y)H(\phi_1(x,y))\mathrm{d}x\mathrm{d}y}{\iint_\Omega H(\phi_1(x,y))\mathrm{d}x\mathrm{d}y}$$

$$c_i^- = \frac{\iint_\Omega u_{0,i}(x,y)\left[1-H(\phi_1(x,y))\right]\mathrm{d}x\mathrm{d}y}{\iint_\Omega \left[1-H(\phi_1(x,y))\right]\mathrm{d}x\mathrm{d}y}$$

$$d_i^+ = \frac{\iint_\Omega u_{0,i}(x,y)H(\phi_2(x,y))\mathrm{d}x\mathrm{d}y}{\iint_\Omega H(\phi_2(x,y))\mathrm{d}x\mathrm{d}y}$$

$$d_i^- = \frac{\iint_\Omega u_{0,i}(x,y)\left[1-H(\phi_2(x,y))\right]\mathrm{d}x\mathrm{d}y}{\iint_\Omega \left[1-H(\phi_2(x,y))\right]\mathrm{d}x\mathrm{d}y}$$

The segmentation result of single color cell image is shown in **Figure 3**. **Figure 3(a)** is the color cell image of being segmented, which is a high-grade squamous intraepithelial lesion (HSIL) cervical cell. **Figures 3(b)-(d)** are the cell image of the red, green and blue channel respectively and we can see that the gray scale value are great different from each other. The segmentation result have been shown in **Figures 3(e)-(h)**, where the red line indicate the contour curve between the cell nuclei and cytoplasm and the blue line the contour curve between the cytoplasm and the background. Where the **Figure 3(e)** is the result of using the method which is proposed in the paper, **Figures 3(f)-(h)** are the result of gray scale cell image segmentation using the modified C-V model.

The conventional color cell image segmentation result is applying gray cell image segmentation in each channel and combined the result together to get the final segmentation result. The cell body, cell nuclei and cytoplasm being segmented by using the traditional method have been shown in **Figures 3(i)-(k)** respectively. While the cell body, cell nuclei and cytoplasm being segmented by using the method proposed in this paper have been shown in **Figures 3(l)-(n)**. We can see that the edges of the cell body and cell nuclei are accurate and smooth than the traditional method, and approve the feasibility of the proposed method.

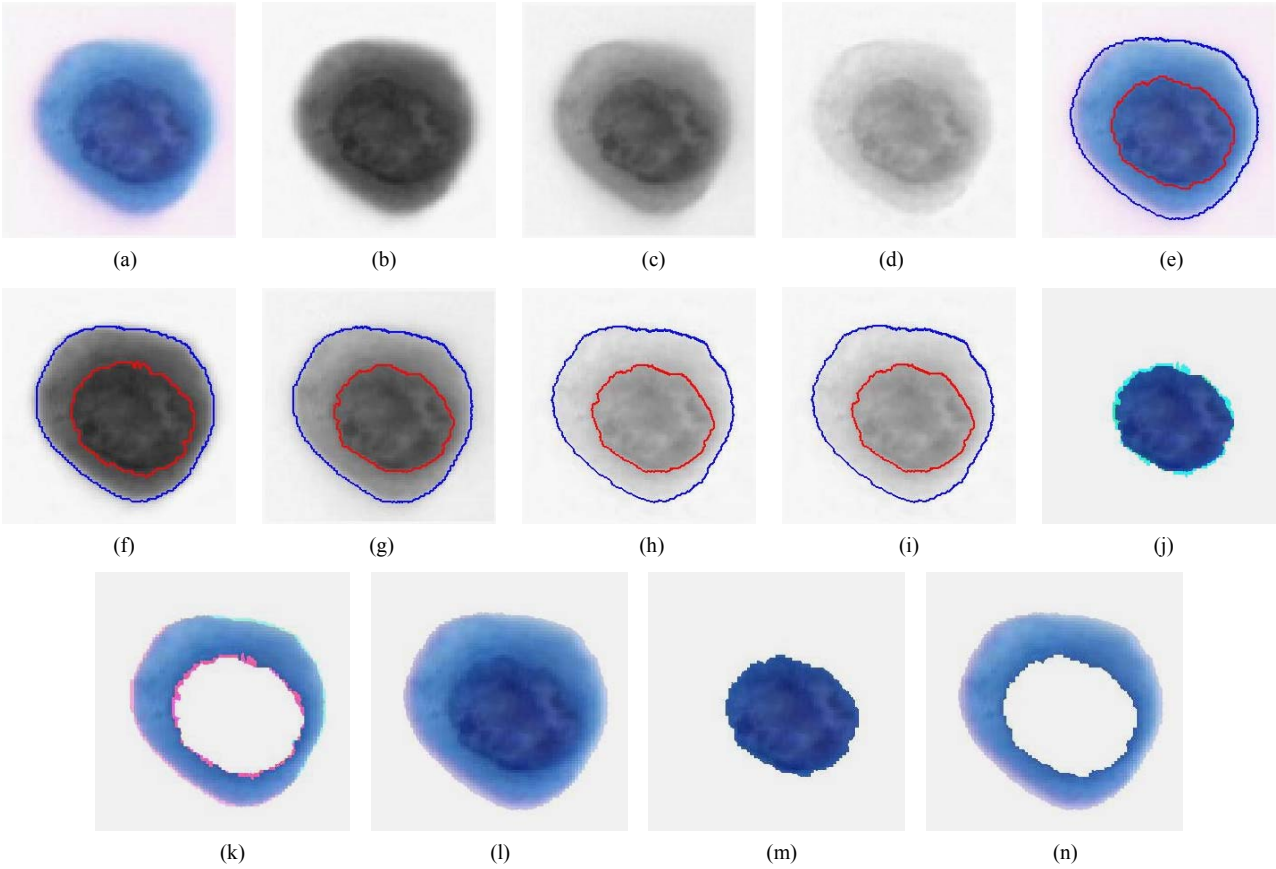

Figure 3. Color cervical cell image segmentation results: (a) Original color cell image; (b)-(d) Red, green and blue channels image of the cell; (e) The contour curve of the cell nuclei and the cell body of the color image using the method proposed; (f)-(h): The contour curve of the nuclei and cell body of the red, green and blue channel; (i)-(k): The extracted cell body, nuclei and cytoplasm using traditional method; (l)-(n): The extracted cell body, cell nuclei and cytoplasm using the method proposed in the paper.

5. Conclusion

This paper develops a color cervical cell image segmentation method to segment the nucleus and cell cytoplasm from a cervical smear image. In this paper, a coarse segmentation method using auto-dual threshold segmentation method has been used firstly and region of interest has been extracted. Then fine segmentation based on modified Chan-Vese model has been used in which two independent level set functions have been used to approximate the boundary between nucleus and cytoplasm and the boundary between cell body and background. On the basis of gray scale cell segmentation method, we proposed a color cell image segmentation method using modified C-V model for vector-valued images. The numerical simulation results are given to demonstrate the validity and accuracy of the proposed method. It's observed that the proposed color cervical cell image segmentation methods provide a good performance even the original image has a vague boundary. Besides cervical smear images, these proposed techniques can be employed to other color mages segmentation.

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