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A STUDY OF CHANGE DETECTION ALGORITHM FOR MEDICAL CELL IMAGES

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Identifying the regions of change in multiple images of the same scene taken at different times is of widespread interest. It has a large number of applications in diverse disciplines including remote sensing, surveillance, medical diagnosis and treatment, civil infrastructure and underwater sensing. In medical image processing applications, change detection is considered as one of the imperative steps in order to detect various cell diseases. We propose a method of change detection in medical cell images which can be used efficiently to diagnose cell anomalies. On the basis of standard deviation calculation of pixels, the discontinuity among the pixel is recorded. Then the image is segmented into a binary image with a fixed threshold where black pixels signify homogeneous region and white pixels denote discontinuity. By comparing the discontinuous regions the changes are detected in the prescribed images. The proposed method is applied over large database of color images both synthetic and real life images. The efficacy of the study is evident from the results.

Keywords: Change Detection in Color Image, Standard Deviation, Threshold Technique, Medical Image Processing.

1. Introduction

Change detection has gained significance over years due to its extensive applicability. The available algorithms for this purpose have been successfully used for region recognition in remotely sensed images [1], [2], [3]. In 2005 RADKE et al. published a comprehensive survey of various change detection algorithms by addressing the problems associated with the work [4]. The identification of changes in medical cell images has always been a challenging task for the researchers. This is due to the complex nature of the acquired images and it becomes more difficult as some unavoidable noise gets added during image registration process. Most of the changes are subtle and not easily differentiable. Thus, the change detection algorithms must have certain degree of efficiency to be granted as acceptable. In 2007, Pornchai Phukpattaranont and Pleumjit Boonyaphiphat proposed a method for segmenting nuclear stained breast cancer cell images. Their approach consists of color categorization using neural network, noise removal and shape simplification using mathematical morphology, and cell size consideration [5]. M. Bosc et al. suggested change detection in multimodal serial MRI with a special application of this method towards multiple sclerosis lesion evolution [6]. Louis Lemieux et al. proposed another method of change detection in MRI of brain lesions. The method is based on the automatic segmentation of structure in the difference images from matched scan pairs [7]. Paul L. Rosin in his paper discussed four threshold techniques based on combinations of noise and signal distribution, which can be used effectively in change detection algorithms [8]. In 2003, Lorenzo Bruzzone and Roberto Cossu published a paper where they concentrated primarily on the noise removal procedures. Their approach was formulated on the framework of the change vector analysis (CVA) technique [9]. Binglong Xie, Visvanathan Ramesh and Terrance Boult proposed a scheme of illumination change detection [10].

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2. Steps of Proposed Method

In this paper, we have discussed a technique of change detection in medical cell images. Here color image is assumed as a data set and each pixel as a data point of that data set. As RGB color model represents high correlation within pixels, we have chosen RGB model for our analysis. Proposed method consists of four distinct steps and they are discussed below.

2.1 Smoothing by Adaptive Median Filter

A traditional median filter is based upon moving a window over an image and computing the output pixel as the median of the gray values within the input window. If the window is J x K in size we can order the J*K pixels in gray level values from smallest to largest. If J*K is odd then the median will be the (J*K + 1)/2 entry in the list of ordered gray values. Median filters are quite popular because, for certain random types of noise, they provide excellent noise reduction capabilities, with considerably less blurring than linear smoothing filters of similar size which helps to preserve edges. The main reason for using adaptive median filter in the present work is that it seeks to preserve detail of the image by smoothing the non-impulse noise, which cannot be removed by the "traditional" median filter [11].

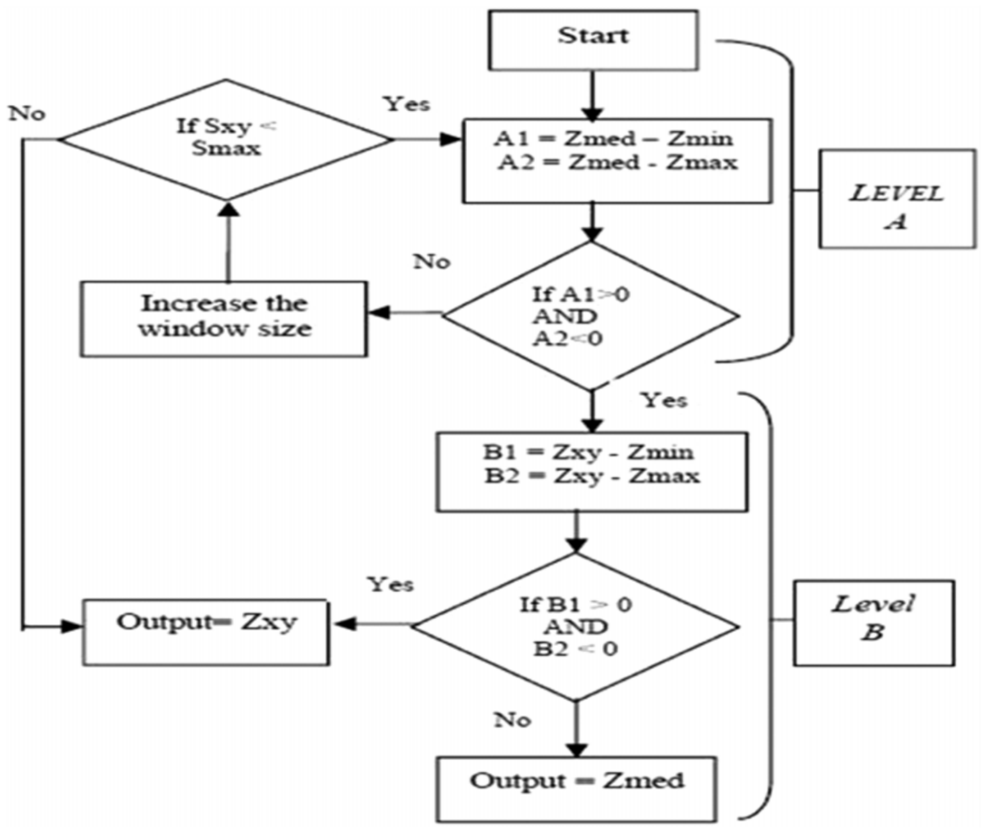

Fig.1: Flow Chart of the Working Steps of Adaptive Median Filter

Where Z_{xy} = gray value at coordinate (x, y), Z_{max} = maximum gray value, Z_{min} = minimum gray value, S_{xy} = window size, S_{max} = maximum allowed window size. Maximum allowed window size for our experiment was 9X9 starting from 3X3 window.

2.2 Standard Deviation Calculation For Discontinuity Measurement

If a region in an image is homogeneous then the RGB values of that region will have a correlation among them and hence a small standard deviation. A low standard deviation indicates that the data points tend to be very close to the same value (the mean); while high standard deviation indicates that the data are "spread out" over a large range of values. Therefore for a particular sub image (3X3 neighborhood considered), if the value of the standard deviation changes significantly from its previous positional value then there is a possibility of existence of a discontinuity. To reduce the computation overhead first, we have calculated a transformed value for each pixel which converts three component valued pixels into a single valued attribute and finally calculated standard deviation over that transformed value.

$$\text{Pixel}(i,j) = \text{Red}(i,j)+2*\text{Green}(i,j)+3*\text{Blue}(i,j) \quad (1)$$

If $x_1, x_2, x_3, x_4 \ldots x_n$ are the transformed values of the pixels then standard deviation (σ) is calculated as follows:

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \bar{X})^2} \quad (2)$$

where n is the no. of points, (here no. of pixels) and $\bar{X}$ is the arithmetic mean of the values x_i, defined as:

$$\bar{X} = (x_1 + x_2 + \ldots\ldots + x_n) \quad (3)$$

2.3 Threshold Technique

Threshold technique is very important task in discontinuity detection algorithms. The accuracy of an algorithm is dependent on the choice of threshold parameters. The criteria of selection of a parameter for a given image are that the resultant should satisfy the following: (i) It should contain most of the prominent changed regions (ii) It should not contain too much unwanted noise (iii) It should be meaningful and visibly pleasing. The proposed method uses a single threshold value T. There are several ways to obtain a fixed parameter value. A very simple way is to observe the outputs for a set of selected images and take that value which is producing acceptable results for all the selected images. When such an experiment is done over large number of selected different kind of images it produced acceptable results for T= 45.

2.4 Change Detection

We process the binary images further through a pixel by pixel comparison method for obtaining the difference image (DI) which will give us our desired changes in the two scenes. By applying the discontinuity measurement and threshold technique, most of the common features of those two images were removed. Hence these two binary images have either black (homogenous) regions or white (discontinuous) regions. Once the difference image was built, the image was further filtered on a higher degree to identify the changed regions distinctly. By superimposing two binary images, pixels those having different values indicated the changed regions.

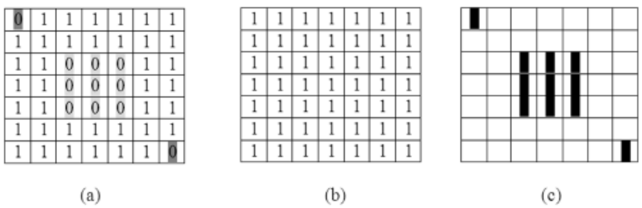

Fig. 2 (a) & (b) Are the Two Binary Images Obtained After Threshold. (c) Image Obtained After DI Calculation

In Fig. 2 (a) green cells denote changed pixels and red cells signify noise. In fig 3(c), all the black cells are detected as changed pixels which are obtained pixel by pixel comparison between Fig. 2(a) and 2(b) and the two corner pixels are generally noise pixels as they do not signify any logical change. In order to remove such inconsistency, we have applied the median filter. Let $X(i) = \{x_1, x_2, x_3...., x_n\}$ and $Y(i) = \{y_1, y_2, y_3...., y_n\}$ are the two vectors which contain the intensity values of two binary images where n is the number of pixels. Now the deviation becomes:

$$\delta(i) = |X(i) - Y(i)| \quad (4)$$

By computing the values of $\delta(i)$, one can easily determine the changed pixels as well as the changed regions.

3. Results and Discussions

The proposed algorithm is tested on large number cell and tissue image data set to judge its stability and accuracy. Here we will present our results obtained from two different cell images. Fig. 3(a) is the normal cell image. Fig. 3(b) shows the same cell image with a short of patch which can be considered as a cell irregularity. Fig. 3(c) & Fig. 3(d) are the discontinuity images of Fig. 3(a) & Fig. 3(b) respectively. Fig. 3(e) is the intermediate difference image which contains spurious noise. So we further processed this output image applying median filter to remove those unwanted noise and finally Fig. 3(f) contains the desired changes (the patches).

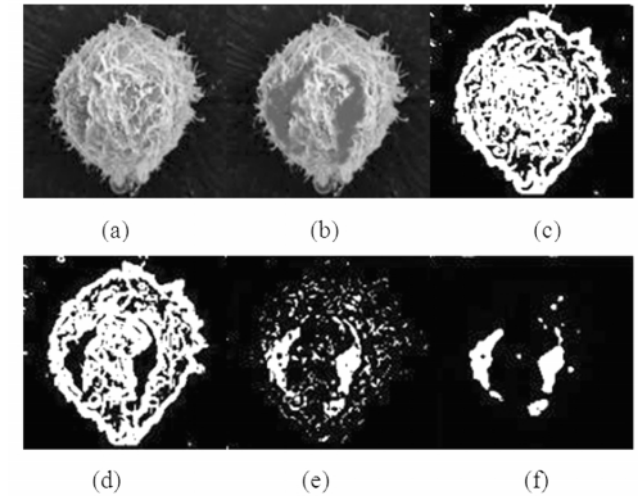

Fig. 3(a) Normal Cell Image Without Patch, (b) Cell Image with Patch has been Developed, (c) Discontinuity Image Without Patch, (d) Discontinuity Image With Patch, (e) Difference Image (DI), (f) Final Output After Removing Noise

Similarly, Fig. 4(a) shows a different cell image. Fig. 4(b) shows its discontinuity image. Fig. 4(c) is the image of the same cell after the patch is predominant; Fig. 4(d) shows its discontinuity image. Fig. 4(e) shows the final noise free change detected image.

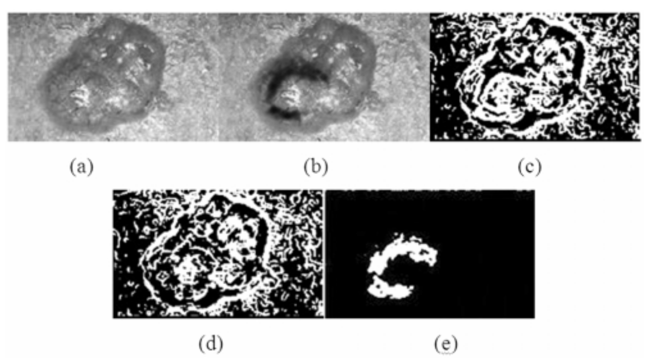

Fig. 4(a) Cell Image Without Patch, (b) Cell Image After the Patch has been Developed, (c) Discontinuity Image Without Patch, (d) Discontinuity image with patch, (e) final output

4. Conclusions and Future Works

The paper presents a Study of Change detection scheme for medical cell images. Proposed method is tested on different images with stable and fairly good results. Consistent acceptable outputs over different kinds of images have demonstrated robustness of the presented scheme. However, if the scenes under consideration have sufficient amount of varied illumination then this algorithm fails to detect the changed regions properly. So, we are continuing our research to eliminate the problem caused by illumination. Also in addition to that, our next venture will be comparing the existing algorithms with the proposed one and analyze the performance on the basis of parameters like computing time, execution complexity and accuracy of the system output in presence of noise.

REFERENCES

[1] Volker Walter, "Object-based Classification of Remote Sensing Data for Change Detection," ISPRS Journal of Photogrammetry and Remote Sensing, 58, Issues 3-4, Integration of Geodata and Imagery for Automated Refinement and Update of Spatial Databases, January 2004, pp. 225-238.

[2] John G. Lyon, Ding Yuan, Ross S. Lunetta, and Chris D. Elvidge, "A Change Detection Experiment Using Vegetation Indices," Photogrammetric Engineering & Remote Sensing, Journal of The American Society for Photogrammetry and Remote Sensing, 64, Number 2, February 1998, pp 143-150.

[3] Susmita Ghosh, Niladri Shekhar Mishra, Ashish Ghosh, "In Proceedings of the 2009 Seventh International Conference on Advances in Pattern Recognition," ICAPR 09, pp. 385-388.

[4] R. J. Radke, Andra S., O. Al-Kofahi, and B. Roysam, "Image Change Detection Algorithms: A systematic Survey," IEEE Transactions on Image Processing, 14, no. 3, pp. 294–307, Mar. 2005.

[5] Pornchai Phukpattaranont, Pleumjit Boonyaphiphat, "Color Based Segmentation of Nuclear Stained Breast Cancer Cell Images," ECTI Transactions on Electrical Eng., Electronics, and Communications 5, No.2 August 2007.

[6] M. Bosc, F. Heitz, J. P. Armspach, I. Namer, D. Gounot, and L. Rumbach, "Automatic Change Detection in Multimodal Serial MRI: Application to Multiple Sclerosis Lesion Evolution," Neuroimage, 20, pp. 643–656, 2003.

[7] L. Lemieux, U. Wieshmann, N. Moran, D. Fish, and S. Shorvon, "The Detection and Significance of Subtle Changes in Mixed-Signal Brain Lesions by Serial MRI Scan Matching and Spatial Normalization", Med. Image Anal., 2, no. 3, pp. 227–242, 1998.

[8] P. Rosin, "Thresholding For Change Detection," Comput. Vis. Image Understanding, 86, no. 2, pp. 79–95, May 2002.

[9] B. Xie, V. Ramesh, and T. Boult, "Sudden Illumination Change Detection Using Order Consistency," Image Vis. Comput., 22, no. 2, pp. 117–125, Feb. 2004.

[10] L. Bruzzone and R. Cossu, "An Adaptive Approach to Reducing Registration Noise Effects in Unsupervised Change Detection," IEEE Trans. Geosci. Remote Sens., 41, no. 6, pp. 2455–2465, Nov. 2003.

[11] Rafael C. Gonzalez, Richard E. Woods, Digital Image Processing, Second Edition.