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Digital Image Processing Technique for Breast Cancer Detection and Analysis

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***Abstract*:** Biopsy is a time consuming process and requires a great deal of skill and experience. Digital image processing techniques can play an important role in helping perform breast biopsies, especially of abnormal areas. In my research work, to understand the type of breast cancer cell and attempt to analyses the histopathological slides with my proposed method to identify cancer parts just using simple technique of isolation of insignificant portion of biopsy slide by color thresholding based segmentation. Many features used in the breast cancer detection and analysis of histopathology image are inspired by clinical pathologists as important for diagnosis and characterization. A large majority of these features are features of cell nuclei in biopsy image; as such, there is often the desire to segment the image into individual cell nuclei. In this paper, present an analysis of the utility of color thresholding method for segmentation of cancer cell nuclei for classification of H&E stained histopathology image of breast tissue. I am showing the cell level classification performance using these segmented nuclei in a benign versus malignant. Results indicate that very good segmentation and classification accuracies can be achieved with color thresholding based segmentation of cancer cell nuclei. The simplicity of algorithm is leads to less computational time. Thus, this approach is suitable for automated real time breast cancer detection and analysis tool.

Keywords: Cancer, Biopsy, Surgical biopsy, Histopathological image, color thresholding, cell nuclei, color segmentation, Bi-color monochrome image and Inverse image.

I. INTRODUCTION

Cancer is a group of diseases that cause cells in the body to change and grow out of control. Most types of cancer cells eventually form a lump or mass called a tumor, and are named after the part of the body where the tumor originates. Breast cancer begins in breast tissue, which is made up of glands for milk production, called lobules, and the ducts that connect lobules to the nipple. The remainder of the breast is made up of fatty, connective, and lymphatic tissue [12]-[13]. Most masses are beginning, that is, they are not cancerous, do not grow uncontrollably or spread, and are not life-threatening. Some breast cancers are called in situ because they are confined within the ducts (ductal carcinoma in situ) or lobules (lobular carcinoma in situ) of the breast. Nearly all cancers at this stage can be cured. Many oncologists believe that lobular carcinoma in situ (also known as lobular neoplasia) is not a true cancer, but an indicator of increased risk for developing invasive cancer in either breast [13]-[14]. Most cancerous breast tumors are invasive, or infiltrating. These cancers start in the lobules or ducts of the breast but have broken through the duct or glandular walls to invade the surrounding tissue of the breast. The seriousness of invasive breast cancer is strongly influenced by the stage of the disease; that is, the extent or spread of the cancer when it is first diagnosed [12]-[21]. Imaging techniques play an important role in helping perform breast biopsies, especially of abnormal areas that cannot be felt but can be seen on a conventional mammogram or with ultrasound.

II. PREVIOUS WORKS

The segmentation of cell nuclei on a cell level in histopathology image is a very difficult and time consuming problem. Many nuclear segmentation algorithms make use of immunostaining for more specific location of cellular structures [15]-[16], the Feulgen stain which is specific to DNA [4]-[8], or even the physical extraction of cell nuclei prior to image acquisition [3]. The use of cytology imagery is more often addressed since this provides a less complicated image structure with more instances of isolated cells and/or well-delineated cell clusters [15]-[17]. The use of automated nuclear segmentation algorithms on standard H&E histology imagery is rarer and has met with mixed success [8, 9]. Semi-automated or even manual nuclear segmentation is still used in some research, even for the more specific Feulgen staining protocol [2–4], immunohistochemical staining [1], and cytology imagery [6]-[17]. This indicates the inherent difficulty in segmentation of nuclei and also indicates the desire for appropriately segmented nuclei for further nuclear-based quantitative analysis (e.g., classification of cancer image). Automated segmentation is more desirable, however, for ultimate use in computer aided diagnosis systems since it does not require extensive user interaction. In this paper, I am investigating the use of color segmented nuclei for the classification of H&E-stained histopathology image of breast cancer. Nowadays many camera-based automatic breast cancer detection systems have to face the problem of cells and their nuclei separation from the rest of the image content (Lee and Street, 2000; Pena-Reyes and Sipper, 1998; Setiono, 1996; Wolberg *et al.*, 1993) [7]- [9]. Nuclei separation process is very important because the nucleus of the cell is the place where breast cancer malignancy can be observed. Thus, much attention in the construction of the expert supporting diagnosis system has to be paid to the segmentation or Breast Cancer detection stage. The main difficulty of the segmentation process is due to the incompleteness and uncertainty of the information contained in the histopathological image. The imperfection of the data acquisition process in the form of noise, chromatic distortion and deformity of histopathological material caused by its preparation additionally increases the problem complexity [6]-[8]. The nature of image acquisition (3D to 2D transformation) and the method of scene illumination also affect the image luminance and sharpness and quality [14]-[15]. Until now many segmentation methods have been proposed (Carlotto, 1987; Chen *et al.*, 1998; Kass *et al.*, 1987; Otsu, 1979; Su and Chou, 2001; Vincent and Soille, 1991) but, unfortunately, each of them introduces numerous additional problems and usually works in practice under given assumptions and/or needs the end-user's interaction/co-operation (Lee and Street, 2000; Street, 2000; Wolberg *et al.*, 1993; Zhou and Pycock, 1997) [8]-[10].Since nowadays many histopathological projects assume full automation and real-time operation with a high degree of efficiency, a method free of drawbacks of the already known approaches has to be constructed. Breast cancer detection, classification of histopathological images is the standard clinical practice for the diagnosis and prognosis of breast cancer. Pathologists perform cancer detection manually under a microscope. Their experience directly influences the accuracy of cancer detection. Variability among pathologists has been observed in clinical practice [7]-[10]. In a large hospital, a pathologist typically handles number of cancer detection cases per day. It is, therefore, a very difficult and time-consuming task. A Computer system that performs automatic cancer detection can assist the pathologists by providing second opinions, reducing their workload and alerting them to cases that require closer attention, allowing them to focus on diagnosis and prognosis. This paper presents a color segmentation method for breast cancer detection and classification. Furthermore, one of the main objectives of computer aided biopsy analysis is to minimize some of the variability's that occur as a consequence of the manual microscopically inspection of stained slides. In addition, computer aided nuclei analysis also has to be efficient, since pathologists are unlikely to spend more time on evaluating a specimen than that required for the routine manual assessments. As already mentioned, in the manual assessment of biopsy slides one strategy has been to utilize a semi quantitative scheme to make the assessment more accurate and more objective. To the best of our knowledge no systems as yet exist which attempt to aid the expert in the cancer cell detection, cancer cell counting, and classification of individual cancer cell nuclei using the semi-quantitative scheme.

III. PROPOSED TECHNIQUE

In the experiments, different breast cancer tissues and different non cancerous breast tissues from different patient and normal females are considered. Each of the 24-bit jpg image size is 447X600 Pixels.

Process1. Detection and classification of cancer cell nuclei in H & E stained histopathology image.

Algorithm:

```
Input: 24-bit color jpg image
R = Red component value in 24-bit color jpg image
G = Green component value in 24-bit color jpg image
B = Blue component value in 24-bit color jpg image
Output:  24-bit color jpg image
Begin
Step1. Open RGB_Image to read
Step2. Open color thresholding image to write
Step3. [X Y Z] = RGB_Image size
Step4. Loop I=0 to X
          Loop j=0 to Y
If (50<R<120)
R=0
Else
R=255
If (0<G<60)
G=0
Else
G=255
If (120<B<180)
B=0
Else
B=255
End of loop
End of loop
Step5. Add R, G, and B component of image
End
```

Process2. Convert the 24-bit color jpg image to 8-bit grey scale image after increasing contrast of the biopsy image.

Algorithm:

```
Input: 24-bit color jpg image
RGB_Image = 24-bit color jpg image
Grey_Image = 8-bit grey image
[X Y Z] = 24-bit color jpg image size
R = Red component value in 24-bit color jpg image
G = Green component value in 24-bit color jpg image
B = Blue component value in 24-bit color jpg image

Grey = Intensity Value
Output: 8-bit grey scale image
Begin
Step1. Open RGB_Image to read
Step2. Open Grey_Image to write
Step3. [X Y Z] = RGB_Image size
Step4. Loop I=0 to X
          Loop J=0 to Y
Read R, G, B from RGB_Image
If (R>150)
R=R*1.5
If (R>255) R=255
Else
```

R=R/1.5
If (R<0) R=0
If (G>150)
G=G*1.5
If (G>255) G=255
Else
G=G/1.5
If (G<0) G=0
If (B>150)
B=B*1.5
If (B>255) B=255
Else
B=B/1.5
If (B<0) B=0
Grey = 0.4 * R+ 0.8 * B +0.48* G
Write Grey to Grey_Image
End of loop
End of loop
Step5. Close RGB_Image, Grey_Image
End

Process3. Convert the resultant 8-bit grey scale image to Bi-Color Monochrome and Inverse Bi-Color Monochrome image after increasing contrast of the biopsy image.

Algorithm:

Input: 8-bit grey image
Grey_Image = 8-bit grey image
Mono_Image = Bi-Color Monochrome image
[X Y] = 8-bit grey image size
Grey = Intensity Value
Output: Bi-Color monochrome image
Begin
Step1. Open Grey_Image to read
Step2. Open Mono_Image to write
Step3. Find threshold value
Step4. [X Y] = Grey_Image size
Step5. Loop I=0 to X
    Loop J=0 to Y
Read Grey from Grey_Image
If (Grey>150)
Grey =R*1.5
If (Grey >255) Grey =255
Else
Grey = Grey /1.5
If (Grey <0) Grey = 0
Write Grey to Mono_Image
End of Loop
End of Loop
Step6. Close Grey_Image, Mono_Image
End

IV. TEST RESULT

In this techniques, to remove the huge amount of fat, connective tissue, and gland tissue from the Cancerous cells within the histopathological biopsy image. The cancer stage, cancer cell intensity, type of cancer and treatment of cancer can only be detected on the basis of orientation of malignant cancer cell in compare with normal cells. The outputs of algorithms are depicted in the following figure for cancerous Figure 1, 2, 3, 4, 5, 6, 7 and 8, shows the Cancerous tissue.

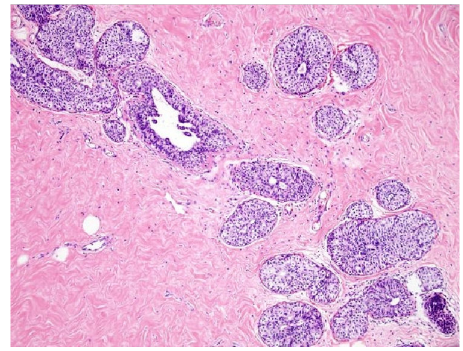

Figure1. Histopatholgical biopsy image

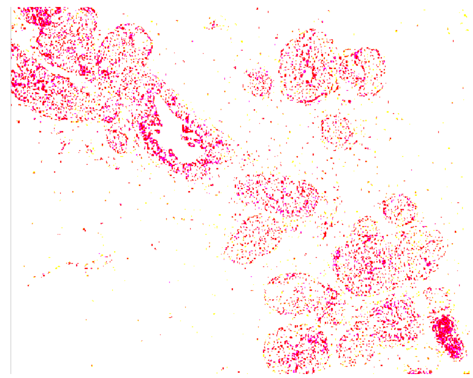

Figure2. Cancer cell detected color image

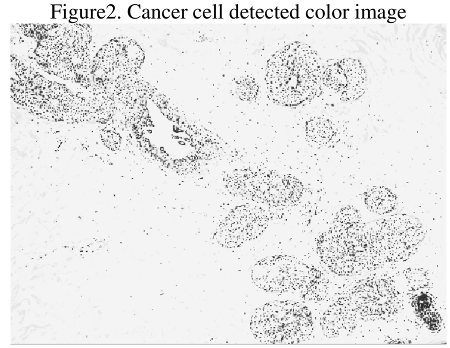

Figure3. Cancer cell detected gray image

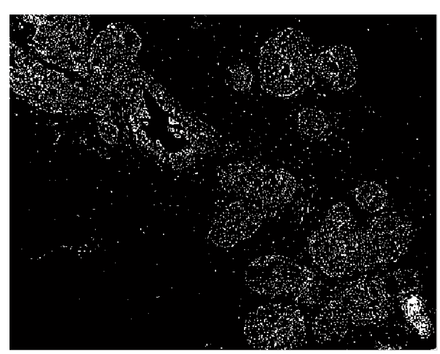

Figure4. Cancer cell detected Bi-color image

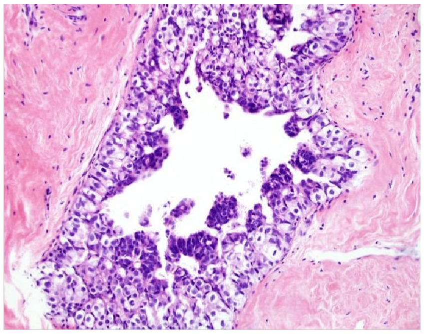

Figure5. Histopatholgical biopsy image

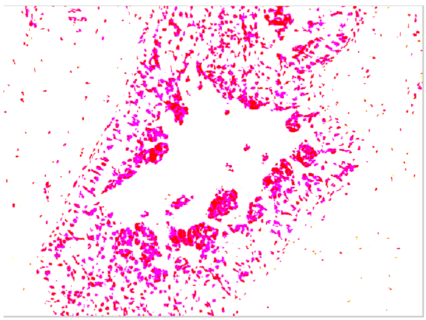

Figure6. Cancer cell detected color image

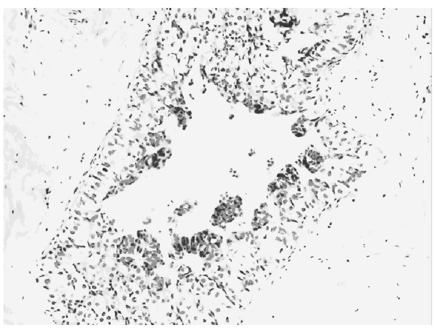

Figure7. Cancer cell detected gray image

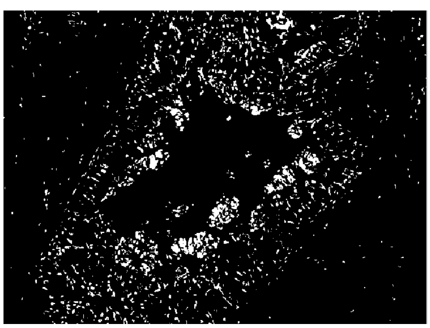

Figure8. Cancer cell detected Bi-color image

In figure 2, 3, 4, 6, 7, 8 all the fat, connective tissue, cancer cell and gland tissue are isolated. It is only showing the cancer cell parts, which are important to determine the cancer. It is depicting the abnormal orientation of cancer malignant. Major objective are isolate less significant parts from the considerable portion of slide. Increase the contrast of the color image for prominence, which is followed by color thresholding based segmentation, which is followed by converting the segmented biopsy image to grey scale. Later converting the grey scale image to inverse bi-color monochromic image totally eliminates the insignificant part of the biopsy image. In figure 2, 3, 4, 6, 7, 8 totally eliminate the insignificant part of the biopsy image. Figure 2, 3, 4, 6, 7, and 8 show only cancer cells.

V. CONCLUSION

It can be very difficult to decide cancer cell and normal cell. It has been demonstrated that the comprehensive set of cell level features used herein are versatile and general enough to elicit important information from segmented cell nuclei. This was demonstrated with cell level classification performance for ground truth nuclei and for several nuclear segmentations. This paper presented a color thresholding based cell level segmentation method for automatic breast cancer detection and classification of histopathological images. The individual cancer cells are detected and classified in the high resolution image frames. I am concluding that that the proposed system gives fast and accurate cancer cell detection and classification of breast tumor.

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