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Result Basis Paper on Detection of Overlapped Glandular Sture for Disease Diagnosis in Human Body

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ABSTRACT-

In the medical field, currently various methods are used for the diagnosis of the cancer. Mostly the cancer specialist uses the gland structure for the diagnosis of the cancer patient. Hence the glandular structure observation is very important for the cancer patient disease diagnosis. For the disease diagnosis purpose we required the microscopic image of the gland. A single gland contains thousands of tissues and cells in it, some of them may be overlapped to each other. In this paper we used the, Saliency Map Method, for the segmentation of the input image given by the user. Then we have used the Visual Signal To Noise Ratio (VSNR) Method, This method is used to detect the overlapped cells and it also plays the important role to separate the overlapped cells. The VSNR method is also helps to detect the various features of the gland like area, eccentricity and the orientation of each cells present and detect the total area covered by cells in that image. from all above observations the pathologist can easily predict the disease.

Keywords: Gland Structure; Cells; Microscopic images; Segmentation..

1. INTRODUCTION

Tissue diagnosis [1] is the very important factor in the modern day medical field. The tissue diagnosis technique helps to detect various diseases easily from the glandular images. For such type of tissue diagnosis the tissue samples are taken from the patients and then these tissue samples are viewed under the microscope by pathologist. As soon as the pathologist get the microscopic image [2] of the gland, then the pathologist create the image of that gland. From that image the pathologist detects the various components which are present in to that image, and these components are very important for the diagnosis [3], because from the actual structure of the glands diseases can be easily detected. Actually the patients which are suffering from the different diseases, such patients gland structures are changed due to the disease causing components. When the glandular structure of the cells/tissues of such patient are observe under the microscope at that time the cells are affected or not is clearly observed.

From all above explanation, it is observe that, the gland structure detection or observation plays vital role in the medical field for the diagnosis of various diseases. In this paper we had used the Saliency map method [4], this method helps to perform the segmentation of the image and it will creates the saliency Map of that related image and also it contains the log spectrum of that same image and it will represent all components which are present into that image. Then we have used the Visual Signal To Noise Ratio (VSNR) method, once the segmentation process is completed then the cells of the gland may be overlapped, to observe such overlapped cells VSNR method helps to extract these overlapped cells from the background image of the gland. Then the VSNR [5] method also helps to count the total number of cells present in to the glandular image. From the original glandular image, the various features of each cells are observe like area, eccentricity and the orientation. These different features are helps to show the actual position of that cells in to the

microscopic image and that will helps to do the diagnosis of the patient for detection of various diseases.

The researchers had worked in both the fields i.e in image analysis as well as the pathology field and recognize the quantitative analysis of pathological images and that's why the current pathological diagnosis is totally depends on subjective opinion of pathologist, also there is requirement of cleared report of the quantitative image of the pathologic slide, such analysis are important not only from the diagnostic perspectives but also for understanding the exact reason of the diagnosis. We have organized this paper in following different sections. Section 2, described the related methods. Section 3, we describe final result, Section 4 presents the Conclusion Remark and Future Work , and at the last section 5 describes the references.

2. RELATED METHODS

I. Saliency Map Method

The first step of the object recognition is the object detection and this will work for the object extraction from the background, but before recognition the actual object is not possible to extract the particular object from that region. To detect such regions the Saliency Map method is used. The Saliency Map method is also used for performing the segmentation of the original glandular image. This method generally consisting of two processes, the first process works in parallel, it is fast but also simple for implementation while the second process works in serial , slow but it is difficult and complex for the implementation. The literature for this implementation is discussed in [6][7]. For getting the Saliency Map some other models are used and that are given as below.

A. *Spectral Residual Model.*

An efficient coding is the particular framework under which the number of mechanisms of visual processing are interpreted. Borlo [8] It is the first proposal of the efficient coding hypothesis that helps to remove the redundancies from the sensor input. The basic principle of the visual system is to suppress the response to frequently occurring features , but at the same time it will keep its accurate features that are created from the norm[9] , hence it will passes the unexpected signals on the later stages of the processing.On the basis of the theory the effective coding technique decompose the image information H(Image) in to two parts as given in the following equation.

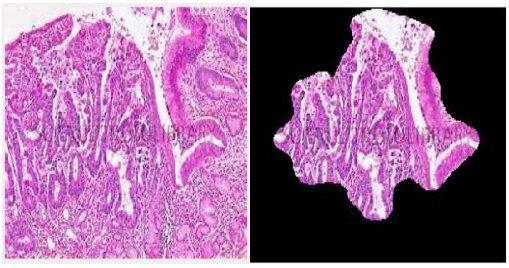
H(Image) = H (Innovation) + H(Priori Knowledge)

Where ,

H(Innovation) represents the Novelty Part of the image, and .

H(Prior knowledge) it will represent the redundant information.

Both the above data are supported by the coding system. The input image and the novelty part is shown in the fig. 1.



(a) Input Image (b) Novelty Part

Fig 1: (a) Original image (b) Novelty Part representation.

B. *Log Spectrum Representation.*

Log Spectrum representation , It will helps us to detect the invariant factors and the scale invariance, properties[10][11]. This property is also known as 1/f law and it represent the amplitude A(f) of the Averaged Fourier Spectrum of the given input image and performs the distribution, as given in the following equation.

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E{A(f)}α 1/f.....1.From the above equation Log Spectrum and Log-Log Spectrum are formed from the input image but the invariance property does not find from the single image. Hence in this paper we only use the log spectrum formation method, to create the actual log spectrum of the image. The input image and the log spectrum formation is shown in the following fig (2).

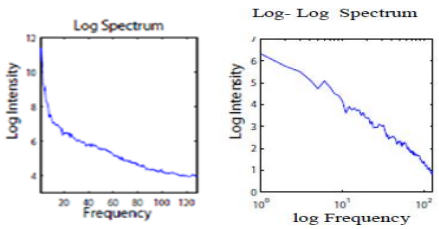
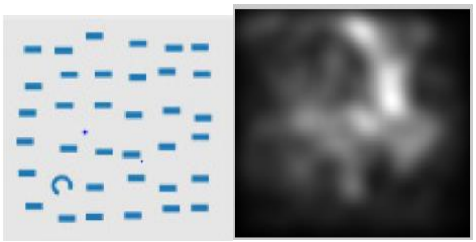


Fig 2: Log Spectrum Representation of the Input Image

C. From Spectral Residual To The Saliency Map

Once the input image is given then the spectral residual method will finds the number of invariance's and redundancies from that image. Then It will creates the many Log Spectrums, The single log spectrum consisting of number curves in it, from all these curves the smoothest and similar curves are detected and then from these curves the proto objects are popped up and it helps to perform the segmentation of the input image, and finally the Saliency map is created. The input image and the Saliency Map of that image is shown in the following fig 3.

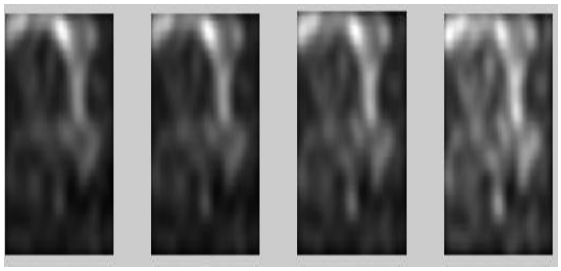


(a) Smooth Curves (b) Saliency Map

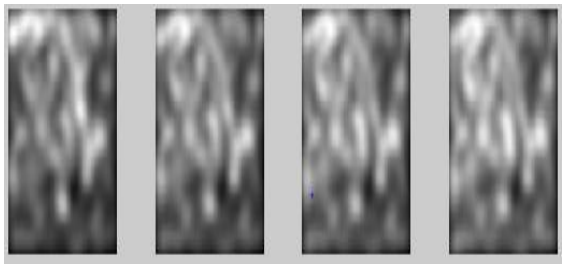
Fig 3: Formation Of Saliency Map From Smooth Curves

II. Conversion of Saliency Image in to Gray Scale Image

Once we get the input image, then that image is converted in to the Saliency Image and the Saliency image contains number of objects. Generally a single image contains number of pixels in it and the some pixels of them are having the more intensities that's why these pixels are brighter than the other pixels, and such pixels are also called as entropy pixels, and these pixels are easy to observe, and at the same time the some pixels do not have the more intensities that's why these pixels are not easily observable, hence to avoid this situation, in this paper we used the conversion of the input image in to the gray scale image, in this process the saliency image is represented in the 8-bit form image. The each scale represent the each and every pixels present in to that plane. In this way the all pixels are easily observable at each levels, as shown in the following fig 4.



Iteration 1 Iteration 2 Iteration 3 Iteration 4



Iteration 5 Iteration 6 Iteration 7 Iteration 8

Fig 4: Conversion Of Input Image Into 8-gray Scale Image

IV. Visual Signal to Noise Ratio (VSNR) Method.

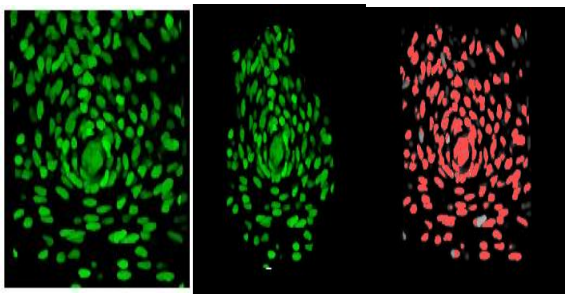
The VSNR method is operated in two steps in the first step , It will determines the distortions present in an image, and then by using the wavelet based model that that having the visual masking and the visual summation, it will determines either any elements are overlapped or not. In the second step, if any distortion is observed and if that distortion is over the threshold [12],[13] then that will operated on low level. Visual property of received contrast and mid level visual property of the global precedence, on the basis of above contents the VSNR method is divided in two steps as given below.

A. Visual Detection And Observation Of Distortion In An Original Image.

It is the first step of the VSNR method in which all the distortions are observed from the input image, on the basis of the following measures. These measures are, first one is detection of distortions in an original image. In the second step detection of suprathreshold in the original image and detection of the effects of suprathreshold on the original image. Once all above measures are taken from the original image, if any other distortions or any kind of noise are remains in an image then by using the Weiner filter these noises are reduced, to get the noise free image.

B. An Actual VSNR.

It is the second step of the VSNR method, In which the different metrics are present and that are helps to represent the Visual Fidelity of distorted image[14] [15] [16]. The metric represent the amount of distortion [17] [18] [19] present in an image. If the distortion is not reduced by the Weiner Filter, Then that original input image is converted in to the black and white image and fill all the holes present in to that image, then we get the well denoised image. Then that denoised image is open. When that image is open at that time the each pixels of that image and all the cells present in to that gland are highlighted and this step will helps us to detect the overlapped glands which are present in to that glandular image as shown in the following fig 5



(a)Original Image (b) Denoised Image (c) Opened image

Fig 5: Denoising of original Image

I. Detection Of Properties Of all the Regions Of Glands.

In the microscopic image of the gland there are number of cells are present and each cells and glands are having the different, from these different characteristics we have implemented some methods to detect the characteristics like area, eccentricity and the orientation. Observation of these characteristics are helps to extract the following important information's. It is shown I the Following fig 6.

- *Area:*

Area of each cells which are present In to the glandular image are helps to detect the an actual size of that cell, or the gland, and also it will helps to detect either that cell or gland are connected to each other or overlapped to another cell or gland.

- *Eccentricity:*

A single microscopic glandular image contains number of cells in it and each are situated in different positions, sometime many glands are situated in the tilted angle, and some of the are present in the concave or in the convex form , so to detect the cells of such situation, we have implement the eccentricity detection method**.**

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- *Orientation:*

Generally in the glandular image number of cells are present and each glands are having the different shapes, to detect the actual shape of these type cells, in this paper we have implemented the orientation method in this paper.

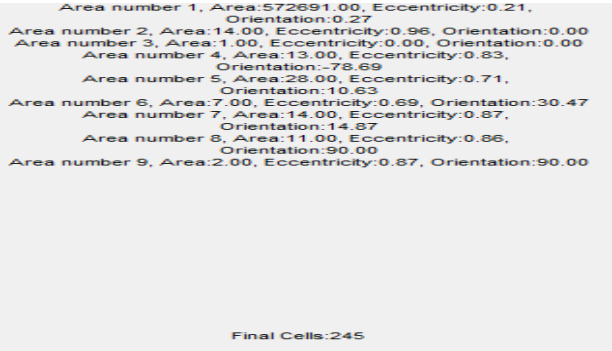

Fig 6: Representation of Properties of the region of the glands like Area, Orientation and eccentricity

3. FINAL RESULT

We have collect the umber of microscopic glandular images, and all the images are of cancerous patients. From these all images some images contains the overlapped cells and some images do not have the overlapped cells. The glandular images which contains the overlapped cells, when these are provided as an input image to our system at that time it will represent all the components and the properties which we have explained above. And the final representation of our system is shown in the following GUI fig 6.

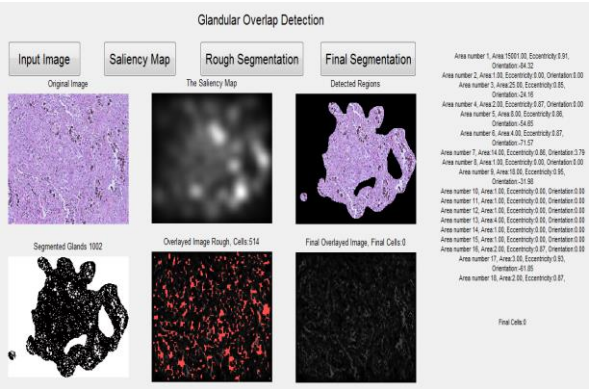

Fig 6: GUI of Overlapped Glandular Detection System.

4. CONCLUSION REMARK AND FUTURE WORK

In summery, in this paper we have implement many methods for detecting the overlapped glandular structures as well as number of cells present in to that glandular image of the cancer patient. In this paper we have used the Saliency Map method to perform the segmentation of the input image. and then we have implement the Visual Signal To Noise Ratio Method to denoising the original image and to detect the overlapped cell or glands from the input image. These methods we have campaired with the number of other methods which are used in this field, but we find that these methods are effective than that of other methods.

The different methods which we have implemented in this paper, there are some limitations, like, it only represent or detect the overlapped cells, area, eccentricity and the orientation but these are not efficient to extract the overlapped cells separately from the original glandular image. So we anticipated that by adding more features to our implementation , then it can boost our implementation ,and in the future the researchers can work improve the results of this system, if these features are added it can produce the globally consistent results.

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