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Prominent Features in Identifying Fibrosis in Microscopic Tissue Images

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Abstract— There are many different features for the diagnosis of fibrosis in Computerized tomographic (CT) images and microscopic Images etc. This paper provides a brief review of prominent features used in identifying fibrosis in microscopic tissue images and the usage of Digital Image Processing in identifying the disease. Traditional methods like unnecessary needle biopsies, manual diagnosis used in identifying the disease require more time, the quality of diagnosis is also bad and having very little reliability. So new methods need to be introduced which helps in diagnosing fibrosis with the help of most prominent features of the disease studied in microscopic images of tissues. In this paper, interest is on the discussion of the prominent features and the usage of automated computerized diagnosis using digital image processing for the recognition of fibrosis. It would enhance the benefits, quality and reliability of diagnosis and how actually it works i.e. different steps involved in the methodology adopted are also summarized.

Keywords—Image analysis, Computer Aided Diagnosis (CAD) System, automated cancer diagnosis, Image Segmentation, Feature Extraction, classification

I. INTRODUCTION

Fibrosis recognition in microscopic tissue images is very challenging because of the lack of knowledge of the most prominent features which help in detection of the fibrosis in microscopic tissue images. It has received extensive attention last two decades, not only because many people are affected with the disease every year which include babies also but also fibrosis recognition is a typical problem whose solution needs to be explored and would help in many other disease classification problems. Fibrosis occurs more speedily in men than in women, and also in elderly people – specially those above age of 50 [1]. It is a tissue disease because when the body's connective tissues becomes injured by inflammation so that they come under attack [2].

Traditionally, diagnosticians use microscopic examination of tissue images of biopsy samples removed from patients, analyse them under a microscope, and make judgments based on their personal experience. While studying such images, a diagnosticians typically assesses the deviances in the cell structures and/or the change in the distribution of the cells across the tissue under scrutiny. However, this assessment is immanent, and often leads to considerable variability [3] [4]. Despite major accomplishments in our understanding the recognition of fibrotic tissues is one of the major research subjects in medical imaging which need to be explored further continues to pose significant challenges. So, to improve the reliability and quality of fibrosis diagnosis and to elude this problem it is essential to develop computational tools for automatised fibrosis diagnosis that facilitates objective mathematical judgment.

Automated cancer diagnosis is not a straightforward task, it has a number of challenges like noise elimination , feature selection, ROI and image segmentation etc to be overcome. So, a tremendous amount of research work has been conducted for automated fibrosis diagnosis.

The CAD algorithm is provided with functions that automatically analyses data acquired and provides patient and tissue diagnosis automatically to identify the suspected regions from images.

Mainly the algorithm consists of two phases i.e An analysis stage and a diagnosis stage.

- In this a computer searches for Region of Interest. So, effected regions are took out and their features are analysed with the help of digital image processing methods.
- In the diagnosing phase, according the extracted features algorithmic rules are decided, and the morbid portions are identified according to defined algorithmic rules. Malignant and benign parts of the diseased are differentiated according to the diagnosed features.

II. OVERVIEW

In this paper, firstly focus is on the prominent features which help in Identifying Fibrosis in microscopic tissue images.

There are many features studied during Computerized aided diagnosis of tissue images. Some are summarized below:-

- **Morphological features:** These Features provide information about the size and shape of a cell [5]. The size of the cell is normally expressed in following terms:

- ***Radius*:** It is the average length of the radial lines towards every boundary points.
- ***Area*:** It is calculated as the sum of all pixels of the segmented nucleus. It is the number of pixels inside the fibroid.
- ***Perimeter:*** It is the length of nucleus envelop. The perimeter is computed by calculating the distance between each adjoining pair of pixels around the border of the region of the cell.
- ***Diameter:*** It is measured and specified by the radiotherapist as horizontal and vertical diameters in centimetres.
- ***Eccentricity*:** It allows to track how much segmented nucleus differs from a healthy nucleus. Healthy nucleus can assume circular shapes and cancerous nuclei can assume arbitrary shapes.
- ***Major axis:*** Major axis is the longest chord that is perpendicular to the minor axis and goes through the center.
- ***MajorAxis:*** Major axis is the longest chord that is perpendicular to the minor axis and goes through the center.
- ***Symmetry:*** *It* is quantified by measuring the length difference between the line segments in opposite directions that are defined to a boundary point and that are perpendicular to the major axis.

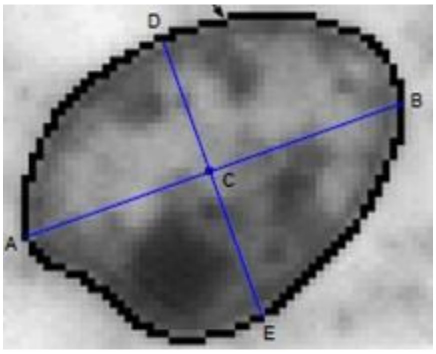

Fig. 1 Diagram showing major axis AB and the minor axis DE.

The statistics based on these properties computed and studied through various researches and it shows that it is used to detect abnormality in a tissue [6] [7] [8].
The measurement of these attributes enables to differentiate the malignant tissues from those of normal ones.

- **Textural features:** Pixels that occurs repeatedly in an image constitute the texture of the image. It is a connected set of pixels which also provides information about the surface variation by quantifying properties such as suavity, granularity, and regularity. It is further divided in two main levels:

    - ***Cellular-level:*** Textural features at this level are extracted by using the co-occurrence matrix or run-length matrix for an single cell [9], [10]. Textural features from the different regions of a cell can also be extracted [11].
    - ***Tissue-level:*** *T*extural features at this level are computed for an entire image or its sub-images [12-13]. Different grain characteristics with different sets of parameters are computed for a single image or sub-image or a cell. For sub-image grain characteristics, the feature sets of the sub-images can be merged to reach a single set for the entire image [14].

- **Cytological Features:** The cytological feature[15] refers to the changes in characteristics of malignant tumor cells and reflect the change in degree of dysplasia and include characteristics like increased in morphological fluctuations in cellular and nuclear size and shape compared to other healthy cells. The malignant tissue have coarse, irregular structure which leads to large nucleoli, increased eccentric figures; chromosomal freakishnesses and cytoplasmic changes.

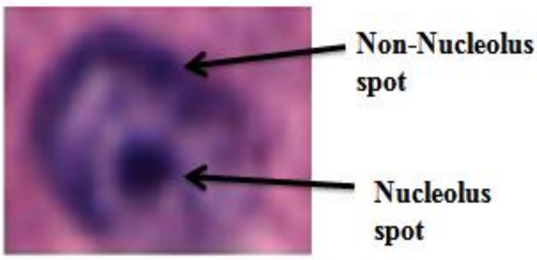

Fig. 2 Diagram showing different spots on the nucleoli

- **Fractal-based features:** The fractal is an object which appears the same at different enlargements and having the self-similarity attribute[16]. It provides information based on the regularity and complexity of a target by measuring its self-similarity level. Fractal analysis is used to understand different phenomena in various biomedical applications including the fibrosis as well as diagnosis [17-18].

The fractal dimension is the most prominent feature for the fractal analysis of a cell or a tissue [19-21]. So fractal feature diagnose is used to differentiate the squares that include malignant cells from those that consist of their similitudes.

The entire image can be diagnosed using above features. It is also possible to directly use the features extracted from the sub-images; these features can be used to classify the sub-images. For instance, Wiltgen et al. extract textural features by splitting the image into squares of sub-images [22]. Subsequently, they use all above explained features are used to recognize the abnormal tissues from healthy ones.

III. GENERIC METHODOLOGY USED IN FIBROSIS RECOGNITON

When an appropriate set of features of are determined, then the next task is differentiate the malignant structures from their similitudes. By looking at the numerous images in their career and use that experience to analyse new medical images radiologists develop potent symptomatic skill. A cell or a tissue is assigned to one of the classes of cancerous or healthy in this phase. Similar images are used as a symptomatic aid in the study of the disease by researchers and doctors. But radiotherapists face many problems if the images are not alike to the unknown morbid tissue image. So, automated computerized schemes are developed by investigators which automatically select alike images from a database on the basis of some defined similarity factors to learn the characteristics of ghoulish tissues [23-24]. This section explains the methodology used and basic steps involved in it which are followed for the recognition of fibrosis.

There are main Seven basic steps included in the proposed automated computer aided diagnosis algorithm for disease detection which are as follows:

- Firstly image is given to the fibrosis recognition system.
- The improvement of digital image quality without knowledge about the source of degradation by image enhancement.
- Segmentation of diseased region using segmentation algorithms from computer tomography images, ultrasonic Images, magnetic Rasonance Images etc.
- Feature extraction from the segmented regions to obtain representative features that can be used to determine the mode of treatment.
- Establishment of diagnosis rules from the extracted features.
- Classification of healthy and abnormal tissue images based on the rules set and classifiers used.

So, the basic aim is to recognise the fibrosis in microscopic tissues by doing morphological, texture, cytological and Fractal based analyses and finding region of interest (ROI) based on special characteristics like size, area, color Intensity, axis etc and then applying image processing and machine algorithms based on various classifiers.

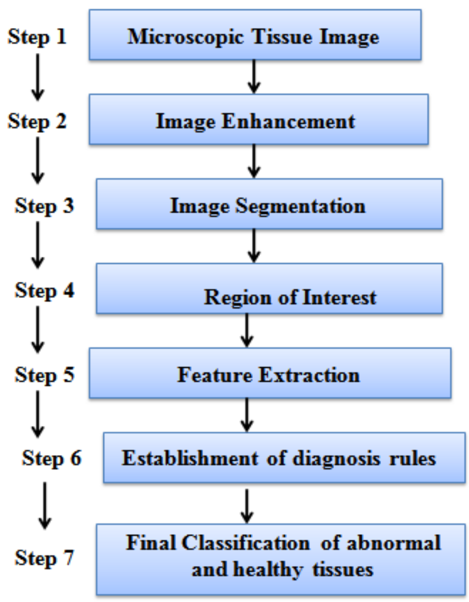

Fig. 3 Fibrosis Detection System

A good exemplification of experiment conducted using computerized aided diagnosis with real time tissues is shown in M.GOMATHI et.al paper [25]. At the final stage of diagnosis patterns are then generated from those images by Feature Extraction and Regional of Interest Properties and finally classification rules are made which further passed to the classifiers for the learning procedure. After learning, a tissue image is given to the proposed automated CAD system. The processing steps will be followed and finally it will detect whether the provided tissue image is malignant or healthy.

The steps are detailed below:-

- **STEP 1: -** It is the initial step of the novel automated system developed. The tissue image to be studied is supplied to the system for extraction of required portions from the microscopic image.
- **STEP 2:-** It is the second step in the methodology adopted. It improves the quality of images for human viewing by removing blur and noise, by increasing contrast, and revealing details.
- **STEP 3:-** Segmentation is implemented to differentiate between normal and abnormal Areas in the tissue images and so malignant tissues are separated from healthy ones based on regional descriptors.
- **STEP 5:-** After segmentation next step is to find out *region of interest* (ROI) which is a portion of an image that is needed to be filtered out. It can be geographical in nature, such as polygons that encompass contiguous pixels [26]. The concept of an ROI is commonly used in medical imaging. For example, the boundaries of a tissue may be defined on an image or in a volume, for the purpose of measuring its size[27]
- **STEP 5:-** Feature Extraction is carried out on the tissue Image after segmentation whose goal is to obtain representative features that can be used to determine the mode of treatment. For instance, if the size of the fibroid is very small, it can be treated by giving medicine, whereas if the size is big, it should be removed by surgery[28]
- **STEP 6:-** After the extraction of features the diagnosis principle can be planned to determine the candidate region precisely. This diagnosis principle can eliminate the fear of delusive recognition of abnormal part and provides better diagnosis.
- **STEP 7:-** This is the final step carried out in the recognition of fibrosis. Diagnosis Rules are defined based on Regional attributes and helps in detecting all malignant regions more accurately. It also helps in ignoring all the false positive morbid parts. At last the affected and Non-affected parts are classified following all above steps and the normal and abnormal potions can easily be separated.

IV. CONCLUSION

Consequently, the knowledge of most prominent features for the recognition of fibrosis are very helpful for doctors in objective practice in the future. This review paper outlines the most prominent features which are involved in studying the fibrosis and also the basic procedure which should be adopted in identifying the disease in microscopic tissue image. But basic procedure followed in recognition of disease is still lagging behind in various aspects. It is still challenging and its accuracy has been an issue of concern. Therefore, if further new and advanced methods like laser capture micro dissection are attached with various classifiers it can give more better and accurate results.

Also, a number of researchers are investigating various kinds of novel CAD algorithms for detecting fibrosis. CAD investigators attempt to develop very useful CAD systems, which can increase automatized diagnosis abilities to detect candidate region. To show that the new approach is highly effectual and it surmounts existing system significantly and gives more effective results, novel approaches for disease recognition in tissues should be developed and also instanced.

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