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Review an Breast Cancer Detection by Using Image Enhancement Techniques and Image Thresholding Methods

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Abstract - The review articles mainly discuss about the existing cancer detection techniques like Image Enhancement Techniques and Image Thresholding Method. Several domains and concepts are used in the detection of cancer. The some other domains used in this detection technique include Direct contrast enhancement methods, Indirect contrast enhancement methods, Wavelet enhancement methods, Adaptive enhancement methods, Fuzzy Means algorithm. Mammogram image has been in use for very long time and much research has been carried out by early researchers.

Key Words: Breast Cancer, Image Enhancement Techniques and Image Thresholding Method.

I. INTRODUCTION

Cancer is a disease that begins in the cells of the body. Under normal conditions, the cells grow and divide depending on the requirement of the body. This orderly process is disturbed when new cells are formed which is not needed by the body and old cells don't die when they should. These extra cells lump together to form a growth called tumor. There are two types of cancer, benign and malignant.

Cancer is the most vicious disease, the cure of which must be the prime target through scientific investigation. The early detection of cancer can be helpful in curing the disease completely. There are several techniques available in the literature for the detection of cancer. Many researchers have contributed their ideas in the detection of cancer. Breast cancer is one of field to be targeted, which is the most common tumor-related disease among women. Diagnosis of breast cancer is not task for a medical expert, owing to many attributes of the disease.

Cancer results from a series of molecular events that fundamentally alter the normal properties of cells. In cancer cells the normal control systems that prevent cell overgrowth and the invasion of other tissues are disabled. These altered cells divide and grow in the presence of signals that normally inhibit cell growth; therefore, they no longer require special signals to induce cell growth and division. As these cells grow they develop new characteristics, including changes in cell structure, decreased cell adhesion and production of new enzymes.

II. IMAGE ENHANCEMENT TECHNIQUES

Image enhancement technique is motivated by the fact that tumors tend to be brighter than their surrounding as given by Tang et al 2009 [1]. The basic idea here is to employ image enhancement methods to improve the contrast of tumor regions. Image enhancement technique has been proposed to improve the quality and readability of mammograms.

III. DIRECT CONTRAST ENHANCEMENT METHODS

Dhawan and coworkers [2] provided a direct contrast enhancement technique for mammographic images in which a neighborhood consisting of a square region of pixels centered on a given pixel, called the center of the neighborhood. A local contrast for each pixel using the average intensities of the center and the surround regions was defined. The contrast value for each pixel was transformed to a new enhancement contrast value using contrast enhancement function and then obtained enhances contrast value was combined with the original image value to produce a new pixel value of the enhanced image. The limitation of this method is, as the spatial as well as gray value resolution (only 6-bit) is low, cancer regions of low contrast cannot be found.

Mohamed and Youssfi [3] illustrated how morphology mathematics operations are applied in the domain of digital image processing. In the sequel they have presented and discussed how a new algorithm based on mathematical morphology operators is able to detect well the microcalcifications in mammograms images. They applied some of these operators to build an algorithm applied on digital images. They have used the erosion operator by reconstruction with isotropic structuring element, followed by the segmentation based by contrast enhancement to find new powerful algorithms. This algorithm is very efficient to detect contrast enhancement to find new powerful algorithm. This algorithm is very

efficient to detect whether the microcalcifications malignant or benign in mammography images. They have also used another algorithm to extract the minima regions from original image. The application of their algorithm on a very fuzzy image leads them to deduce that their method was very powerful to detect really well the micro calcification.

IV. Indirect Contrast Enhancement Methods

Laine coworkers [4] provided a method using multiscale wavelet enhancement for mammographic image enhancement. In this the authors investigated mammographic image enhancement over complete multiscale representation and the coefficients in each sub band of the multi scale representation were modified using a nonlinear mapping. Three multi scale representations were investigated, including the wavelet transform, the transform and the hexagonal transform. From the results it is identified that wavelet based image processing algorithms could play an important role in improving the performance of digital mammography. The drawback of this method is that the parameters in the nonlinear mapping at each scale are global, which are not optimal.

V. Wavelet Enhancement Methods

The method developed by Dominguez and Nandi [5] selected for the approach of finding cancer in mammogram image. Since it increased the signal to noise ration of the lesions being detected and eliminated the false-positive findings. They had proposed an algorithm for enhancement of mammograms which had the objective of improving him segmentation of distinct structures in mammograms. The enhancement algorithm used wavelet decomposition and reconstruction, morphological operations and local scaling. After enhancement, the segmentation of regions was performed and a set of features were computed from each of the segmented regions. A ranking system was used for classification.

Ireaneus Anna Rejani and Thamarai Selvi [6] proposed a tumor detection technique from mammogram. Their approach focuses on the solution of two problems: Detection of tumors as suspicious regions with a very weak contrast to their background and extraction features which categorize tumors. The tumor detection approach follows the technique of (a) Mammogram enhancement (b) The segmentation of the tumor area (c) The extraction of features from segmented tumor area (d) the use of Support Vector Machine classifier. The improvement is the alteration of the image quality to a better and further understandable level. The mammogram enhancement process consists of filtering, top hat operation and discrete wavelet transform. Then the contrast stretching is used to raise the contrast of the image. The segmentation of mammogram images plays a key role to enhance the detection and diagnosis of breast cancer. The well- known segmentation approach used is thresholding. The features are extracted from the segmented breast area. Next stage categorizes the region using the Support Vector Machine classifier. The approach was tested on 75 mammographic images, from the mini-MIAS database. This approach obtained a sensitivity of 88.75%.

Balakumaran and coworkers [7] were stated that microcalcifications in mammogram have been mainly targeted as a reliable earliest sign of breast cancer and their early detection is vital to improve its prognosis. Since their size is very small and may be easily overlooked by the examining radiologist, computer-based detection output can assist the radiologist to improve the diagnostic accuracy. They have proposed an algorithm for detecting micro calcification in mammogram. The proposed micro calcification detection involves mammogram quality enhancement using multiresolution analysis based on the dyadic wavelet transform and micro calcification detection by fuzzy shell clustering. It may be possible to detect nodular components such as micro calcification accurately by introducing shape information. The effectiveness of the proposed algorithm for micro calcification detection was confirmed by experimental results.

VI. Adaptive Enhancement Methods

Kim et al 1997 [8] proposed an adaptive image enhancement method based on the first derivative and local statistical. In this method, film artifacts that could be misread as cancer were removed and the important features of the mammographic image were enhanced by adding the adaptively weighted gradient images.

Cheng and Xu 2002 [9] presented an adaptive fuzzy logic contrast enhancement method for mammographic images. The method was based on the maximum fuzzy entropy principle. It transformed the image to a fuzzy domain and then, a local measure of contrast, called fuzzy entropy in the fuzzy domain, was computed. The contrast was enhanced using both global and local information. Finally, the enhanced image was obtained using defuzzification, by which enhanced mammogram was transformed back to the spatial domain from the fuzzy domain.

Kang et al 2006 [10] stated that microcalcification is an important part of early breast cancer detection. The authors have proposed a microcalcification detection algorithm using adaptive contrast enhancement in a mammography Computer-Aided Diagnosis (CAD) system. The proposed micro calcification detection algorithm includes two parts. One is adaptive contrast enhancement filtering parameters are determined bas4ed on noise characteristics of the mammogram. The other is multi-stage micro calcification detection. The results have shown that the proposed micro calcification detection algorithm is much more robust against fluctuating noisy environments.

VII. Image Thresholding Method

Davis and Dance [11] proposed a method for detection of cancer. They first detected suspicious regions by a local threshold. Those regions were limited by size criteria and those with an irregular shape were detected. A nearest neighbor cluster method was used to find significant groups. This method shows suspicious regions.

Lai et al 1989 [12] presented a method for detecting breast tumor in mammograms. It relies on a combination of criteria including the shape, brightness contrast and

uniform density of tumor areas. The method used modified median filtering to enhance mammogram images and template matching to detect breast tumors. In the template-matching step, suspicious areas were picked by threshold values and a percentile method was used to determine a threshold for each film. The limitation of the methods presented above is that they concerned only with the localization of the suspicious areas and no attempt is made by them to further classify these areas.

Kom et al 2007 [13] proposed a tumor algorithm that first used a linear transformation filter algorithm to enhance the image; the enhanced image was subtracted from the original image to obtain a differential image. A local adaptive thresholding was developed to detect the mass in the differential image.

VIII. Adaptive Thresholding Method

Hatanaka et al 2001 [14] described an approach that uses an adaptive threshold technique for detecting tumor. The partial loss masses were identified by their similarity to a sector form model in the template matching process. To calculate the similarity, four features were applied: average pixel value; standard deviation of pixel values; standard correlation coefficient defined by the sector form model and concentration feature determined from the density gradient.

Bagci and Cetin [15] presented a method for computer-aided diagnosis of microcalcification clusters in mammogram images. Microcalcification clusters which are an early sign of breast cancer appear as isolated bright spots in mammograms. Therefore they correspond to local maxima of the image. The local maxima of the image were first detected and they were ranked according to a higher-order statistical test performed over the sub band domain data.

IX. Fuzzy Means Algorithm

Brzakovic et al 1990 [16] developed a work in which the analysis of mammograms was performed in two stages. First the system identifies pixel grouping that may correspond to tumors. Next detected pixel grouping were subjected to classification. The essence of the first processing stage was mute resolution image processing based on fuzzy pyramid linking. The second stage employed a classification hierarchy to identify normal (or) tumor. The classification hierarchy was organized in such a way that, the simplest measurements were used at the top and the system steps through the hierarchy only when it cannot classify the detected pixel grouping with certainty. This work concentrates on recognition of two general classes of tumors: benign-non cancerous lesions and malignant-cancerous lesions. These classes of tumors were characterized by a variety of symptoms and in their work it was considered that malignant lesions were star shaped, round nodular-ill-defined with translucent ring of dehydration. Benign lesions were round and well-shaped. The objective of first processing stage of automation of mammogram analysis was to identify possible tumors in mammograms. The heart of the process was fuzzy pyramid linking. Identification of possible tumors was a very difficult task due to the variations of gray level intensities in digitized mammogram. This approach first identified pixel grouping that had different intensity properties and then, decided if they were tumors.

A novel texture analysis approach based on fuzzy co-occurrence matrix concept was proposed by Cheng et al 1995 [17]. This system is used to deal with early and accurate breast cancer diagnosis by analyzing the microscope-slide biopsy images. A novel feature extraction algorithm is used to extract the features from the digitized images, and then the extracted features were given as input to a multilayer back-propagation neural network to categorize the images in to three risk groups. The performances of the conventional cancer diagnosis methods and the proposed algorithm were evaluated and it was found that, this approach has higher performance compared to the existing methods. The proposed technique has wide applications in the areas of pattern recognition and image processing.

Punam Saha et al 2001 [18] indicated that breast cancer risk is associated with mammographic densities. An objective, repeatable, and a quantitative measure of risk derived from mammographic densities will be considerable use in recommending alternative screening paradigms and/or preventive measures. However, image processing efforts toward this goal seem to be sparse in the literature, automatic and efficient methods do not seem to segment dense tissue regions from fat within breasts from digitized mammograms using scale-based fuzzy connectivity methods. Different measures for characterizing mammographic density were computed from the segmented regions and their robustness in terms of their linear correlation across two different projections-cracino-caudal and medio-lateral-oblique were studied. The accuracy of the method was studied by computing the area of mismatch of segmented dense regions using the proposed method and using manual outlining. A comparison between the mammographic density parameter taking in to account the original intensities and that just considering the segmented indicates that the former may have some advantages over the latter.

Jiang et al 2005 [19] proposed a method, in which a structure tensor operator was produced and then applied to each pixel of the mammographic images, which resulted in an Eigen image. The Eigen image was combined with the fuzzy image, which was obtained by a fuzzy transform from the original image to enhance the contrast. Sang-Hyun Hwang et al 2007 [20] proposed a new methodology for medical diagnosis on fuzzy clustering and parallel neural networks. Intelligent systems have various fields. Breast cancer is one of field to be targeted, which is the most common tumor-related disease among women. Diagnosis of breast cancer is not task for a medical expert, owing to many attributes of the disease. So they have proposed a new method, Fuzzy c- means clustering method based parallel neural networks to handle difficult cases. Fuzzy c-means clustering method based parallel neural networks composed of two parts. One is designing the multiple neural networks using classified data by Fuzzy c-means clustering method. The proposed

methodology was experimented, evaluated and compared the performance with other existed models. As a result they have shown the effectiveness and precision of the proposed method are better than other previous models.

X. CONCULSION

Early detection of breast cancer is of utmost importance, since only localized cancer is deemed to be treatable and curable, as opposed to metastasized cancer. Here we have mainly discussed about the existing cancer detection techniques like Image Enhancement Techniques and Image Thresholding Method. Image enhancement technique has been proposed to improve the quality and readability of mammograms. The wavelet enhancement algorithm used wavelet decomposition and reconstruction, morphological operations and local scaling. After enhancement, the segmentation of regions was performed and a set of features were computed from each of the segmented regions. A ranking system was used for classification. The heart of the Fuzzy Means algorithm was fuzzy pyramid linking. Identification of possible tumors was a very difficult task due to the variations of gray level intensities in digitized mammogram. This approach first identified pixel grouping that had different intensity properties and then, decided if they were tumors.

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