International Journal of Emerging Technology in Computer Science & Electronics (IJETCSE)
ISSN: 0976-1353 Volume 21 Issue 1 – APRIL 2016.

DETECTION AND PREVENTION OF BREAST CANCER USING ULTRASOUND IMAGE IN SURF TECHNIQUE

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***Abstract*-Breast cancer is the second leading cause of death for women worldwide, and more than 8% of all women will suffer this disease during their lifetime. In recent years, many women had died due to the presence of breast cancer. Computer-aided diagnosis of masses in ultrasound images is important to the prevention of breast cancer. we propose a suitable method for diagnosis of affected masses. Specifically, for a query ultrasound SURF (speed up robust feature) are extracted. The purpose of this study could be mainly to prove and to demonstrate the possibility of surveying precisely the changing characteristics of a breast cancer lesion within a considered ultrasound images' sequence.**

***Key terms* –Breast Cancer Ultra Sound Images sequence, Feature extraction, Image segmentation, Lesion Characterization, Speckle reduction**

I. INTRODUCTION

Modern digital technology has made it possible to manipulate multi-dimensional signals with systems that range from simple digital circuits to advanced parallel computers. The goal of this manipulation can be divided into three categories:

- Image Processing image in → image out
- Image Analysis image in → measurements out
- Image Understanding image in → high-level description out

The fundamental concepts of image processing. Space does not permit us to make more than a few introductory remarks about image analysis. Image understanding requires an approach that differs fundamentally from the theme of this book. Further, we will restrict ourselves to two–dimensional (2D) image processing although most of the concepts and techniques that are to be described can be extended easily to three or more dimensions. Readers interested in either greater detail than presented here or in other aspects of image processing are referred to Image Processing Fundamentals We begin with certain basic definitions. An image defined in the "real world" is considered to be a function of two real variables, for example, a(x, y) with a as the amplitude (e.g. brightness) of the image at the real coordinate position (x, y). An image may be considered to contain sub-images sometimes referred to as regions– of–interest, ROIs, or simply regions. This concept reflects the fact that images frequently contain collections of objects each of which can be the basis for a region. In a sophisticated image processing system it should be possible to apply specific image processing operations to selected regions. Thus one part of an image (region) might be processed to suppress motion blur while another part might be processed to improve color rendition. The amplitudes of a given image will almost always be either real numbers or integer numbers. The latter is usually a result of a quantization process that converts a continuous range (say, between 0 and 100%) to a discrete number of levels. In certain image-forming processes, however, the signal may involve photon counting which implies that the amplitude would be inherently quantized. In other image forming procedures, such as magnetic resonance imaging, the direct physical measurement yields a complex number in the form of a real magnitude and a real phase. For the remainder of this book we will consider amplitudes as real or integers unless otherwise indicated.

The Purpose of the study could be mainly to prove and to demonstrate the possibility of surveying precisely changing the characteristic of a breast cancer lesion that could image from a consider Ultrasound images sequence. The would justify hence the clinical need for a system permitting flexible and convivial clinical analysis of multi slices Ultrasound breast cancer lesion with greater precision.

Fig. 1 Breast Cancer Image.

II. PREPROCESSING AND SEGMENTATION PROCESS

The proposed Ultrasound sequence would be based merely on features extraction and mainly morphological and textural once. Before features extraction process from consider sequence, In that image pre-processing and image segmentation are involved. The images are filtered in pre-processing technique
TWO METHODS:

- Averaging filter
- Equalization (Adaptive histogrammic equalization)

The main goal of the pre-processing is to improve the image quality to make it ready to further processing by removing or reducing the unrelated and surplus parts in the background of the mammogram images Mammograms are medical images that complicated to interpret. Hence pre-processing is essential to improve the quality. It will prepare the mammogram for the next two-process segmentation and feature extraction. The noise and high frequency components removed by filters.

A. Average filter

The goal of the mean filters used to improve the image quality for human viewers. In this, filter replaced each pixel with the average value of the intensities in the neighborhood. It locally reduced the variance, and easy to carry out Limitations of average filter

I. Averaging operations lead to the blurring of an image, blurring affect features localization.
II. If the averaging operations applied to an image corrupted by impulse noise, the impulse noise attenuated and diffused but not removed.
III. A single pixel with a very unrepresentative value affected the mean value of all the pixels in neighborhood significantly.

B. Equalization

The histogram equalization algorithm has been a conventional image enhancement algorithm for its simplicity and efficiency. It adjusts the gray level of an image according to the probability distribution function of the image and enlarges the dynamic range of the gray distribution to improve visual effects of the image. The histogram equalization algorithm may be divided into two types: local histogram equalization and global histogram equalization. The local histogram equalization may well enhance local details of the image and it may be divided into three types: overlapping sub-block, non overlapping sub block, and partially overlapping sub-block. The non overlapping sub-block method is very rarely used for its obvious square effects; the overlapping sub-block method is also not used in practice for its large amount of calculation and low processing speed; the partially overlapping sub-block method can speed up the calculation, but it is relatively complex enhancing effects. To improve enhancing effects many improved algorithm. Based on the conventional histogram equalization algorithm and the prophase study of and we analyze the relationship of the mapping gray level and introduce the definition of different gray level, gray threshold setting and identification methods. Then, we use the information entropy as the target function to get parameter ù in the gray level mapping formula. According to the threshold, the improved algorithm may automatically identify the gray level of the image and adaptively adjust the spacing of two adjacent gray levels in the new histogram. Thus, it may effectively improve visual effects for any age under the premise of the same information entropy.

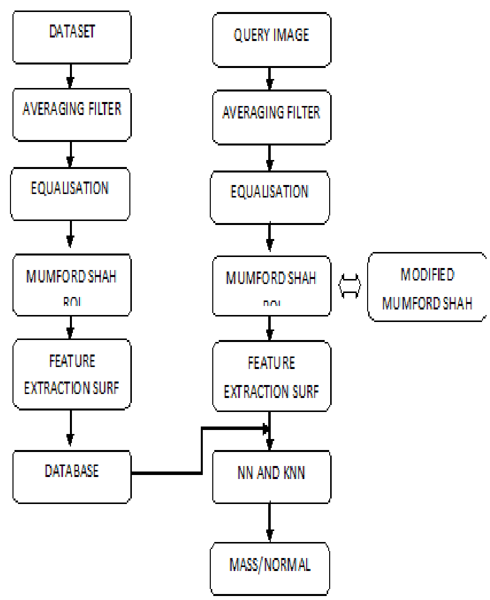


Fig. 2 Block Diagram of Breast cancer

III. TEXTURE FEATURES EXTRACTION

Texture features are extracted as the characterization of breast tumor. The SURF standardized the descriptions of these features as a lexicon and grouped them into three classes: lesion boundary, echo pattern, and posterior acoustic feature class.

A. Lesion Boundary Class

The boundary of a breast lesion could be characterized by an abrupt interface or an echogenic halo. An abrupt interface signifies that the sharp demarcation between the lesion and its surrounding tissue may be discernable or marked by a well-defined, distinct and echogenic line. On the contrary, an echogenic halo signifies that there is no abrupt boundary between the lesion and its surrounding tissue which are connected by an echogenic transition zone.

Fig 3 Feature Extraction

The echo pattern class is based on the study of the lesion echogenicity which could be anechoic, isoechoic, hyperechoic, hypoechoic, or complex.

Echo pattern class could be determined by studying the texture which plays an important role in the differentiation between lesions in breast ultrasound imaging. In fact, texture variation in ultrasound images has been considered as useful feature to identify benign and malignant tumors. However, according to subjectives observations and individual experiences, radiologists may attribute qualitative texture characteristics differently. Therefore, a computed texture analysis is necessary to get quantitative information's on lesion texture. We focus in this work on the quantification of characteristics related to average, variance, and contrast based on the improved Spatial Gray Level Dependence Matrices (SGLDM) method.

B.Posterior acoustic feature class

Posterior acoustic features represent the attenuation characteristics of a lesion with respect to its acoustic transmission. Such a lesion may present an enhancement, a shadowing, or a combined aspects. Similarly, we should note that in some cases of breast lesion there is an absence of posterior acoustic features.

The *mw* width of this area is defined as the two-thirds of the mass width. At both posterior area sides a gap of one sixth of the mass width is preserved for the edges leakage. The height of this area is equal to the height of the mass but should not exceed one hundred pixels.

Fig 4.Feature extraction

C.Mumford shah:

1. Few boundary values are considered for minimization problem in segmentation
2. Smooth approximation is calculated in a time dependent scheme.
3. Only one level set function can be used for region forming.

D.Piecewise-Smooth Mumford and Shah:

1. All boundaries are traced to reduce minimization problem.
2. Euler–Lagrange equations are derived in a time dependent dynamical scheme.
3. Two or more level set functions are used where region forming of the image could not be represented by the boundary.

E.Neural Network:

Weight calculation is performed for input image.

Only single hidden layer is analyzed with the weight parameter. Up to this step we can confirm that features extraction should be performed on multiple slices of the same mass to get more accurate diagnosis. In fact, features extraction performed on one chosen slice could be a major source of error. In fact, the slice choice varies from one radiologist to another. On the other hand, we found that analyze will be restricted to one slice and ignore the other ones which may contain more and even different information. This achieving is motivating to test the developed method on big dataset allowing thus an objective quantitative validation via ROC analyses.

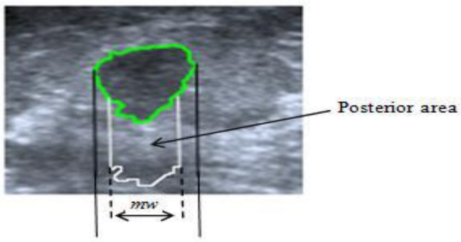
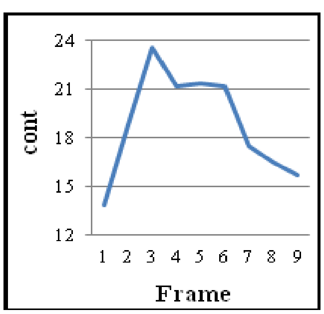
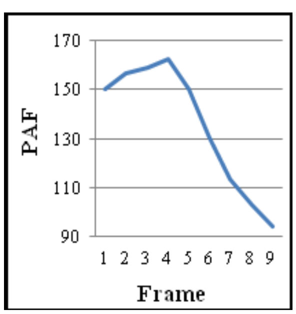


FIG 5. Calculation of the posterior area

IV. CONCLUSION

In this process the Ultrasound image where identified and segmented and different slices using SURF(speed up Robust Feature) rectifies the tumor input performance. For that reason, three steps were needed. The first step consists on the image preprocessing to reduce speckle noise and enhance image quality. The second step is the image segmentation to locate the suspicious areas. The third step permits the extraction of the morphological and textural features that characterize the mass.
Through the analysis of one ultrasound breast images' sequence involving benign mass, we could easily notice that the considered lesion form could change depending on the treated slice, as well as the values' differences for the morphological and the textural features.
In fact, we could clearly note the feature values' differences between all slices which allow us to extract more information about breast lesion characteristics. This would help considerably and essentially when the same lesion may present at the same time slices showing signs of benignity and slices showing signs of malignancy. It should be noted that feature values fluctuation can give an idea about the efficiency of some feathers for tumor characterization or classification.





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