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DETECTION OF BREAST ASYMMETRY USING ANATOMICAL FEATURES-A REVIEW

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***Abstract*:** Radiologists can use the differences between the left and right breasts, or asymmetry, in mammograms to help detect certain malignant breast cancers. An image similarity method is introduced to make use of this knowledge base to recognize breast cancer. Image similarity is determined using a contextual and then a spatial comparison. The mammograms are filtered to find the most contextually significant points, and then the resulting point set is analysed for spatial similarity. An image similarity method is introduced to make use of this knowledge base to recognize breast cancer. We review analysis of breast asymmetry and thus asymmetry is a measure that can play an important role in significantly improving computer-aided breast cancer detection systems.

***Keywords*:** Computer-Aided Detection, asymmetry, image similarity, and breast cancer

INTRODUCTION

Breast cancer is the most common cancer in women. Early detection and diagnosis of breast cancer facilitated with digital mammography can increase survival rate and chances for patient's complete recovery. Bilateral asymmetry is one the breast abnormalities that may indicate breast cancer in early stage of its development. Researchers have been investigating and developing image processing algorithms that may help radiologists in giving accurate diagnosis. Most detection algorithms indicate suspicious regions that may need a better observation. This paper presents a survey of algorithms that have been developed for bilateral asymmetry detection. An overview of algorithms for alignment of the left and right breast is given and methods for comparison of the left and right breast are presented.

Breast asymmetry is an important radiological sign of cancer, this paper describes the first approach aiming to detect *all* types of asymmetry; previous asymmetry-based research has been focussed on the detection of mass lesions. The conventional approach is to search for brightness or texture differences between corresponding locations on left and right breast images. Due to the difficulty in accurately identifying corresponding locations, asymmetry cues generated in this way are insufficiently specific to be used as prompts for small and subtle abnormalities in a computer-aided diagnosis system. We have undertaken studies to discover more about the visual cues utilized by radiologists.

Breast cancer represents 10% of all cancers diagnosed worldwide annually and constituted 22% of all new cancers in women in 2000, making it by far the most common cancer in women. Detection and diagnosis of breast cancer in early stages of development increases possibility of successful treatment and increases chances for complete recovery of the patient. For early breast cancer detection one of the best examination procedures is still mammography.

Mammographic screening programs have reduced mortality rates by 30-70% . In mammographic images early signs of breast cancer, such as bilateral asymmetry, can be revealed. Bilateral asymmetry is asymmetry of the breast parenchyma between corresponding regions in left and right breast. According to ACR's (American College of Radiology) Breast Imaging Reporting and Data System there are two types of bilateral asymmetry: global asymmetry and focal asymmetry.

Global asymmetry is defined when a greater volume of fibroglandular tissue is present in one breast compared to the corresponding area in the other breast and focal asymmetry is circumscribed area of asymmetry seen on two views, but it lacks the borders and conspicuity of a mass. Focal asymmetry is usually an island of healthy fibroglandular tissue that is superimposed with surrounding fatty tissue. Asymmetric breast tissue can be expected in approximately 3% of the population. Asymmetric breast tissue is usually benign, but an asymmetric area may indicate a developing mass or an underlying cancer. Thus, asymmetrical breasts could be reliable indicators of future breast disease in women and this factor should be considered in a woman's risk profile.

Asymmetries of concern are those that are changing or enlarging or are new, those that are palpable and those that are associated with other findings, such as microcalcifications or architectural distortion. Radiologist compares left and right mammographic images searching for visual cues that may indicate presence of breast lesion. Radiologist's misinterpretation of the lesion can lead to a greater number of false positive cases. 65-90% of the biopsies of suspected cancers turn out to be benign. Thus, it is important to develop a system that could aid in the decision between follow-up and biopsy.

REVIEW WORKS

Peter Miller and Sue Astley [1] made the assertion that asymmetry is detected by comparing anatomically similar regions of the left and right breast. They propose that a successful automated system can be developed using the same principle. Firstly, tissue types in the digitised mammogram are segmented to form anatomically homogeneous fat or non-fat regions. Asymmetry is then detected by comparing various features of non-fat regions in the left and right mammogram. Finally, the evidence from these comparisons is combined, in order to classify the case as normal or abnormal, and to locate any suspicious regions. The main advantage of this approach over conventional methods is that the non-fat regions are extracted from the mammogram and compared directly, so asymmetry measurements are likely to be more robust than those obtained using problematic breast alignment procedures. It is also possible to compare the *shape* of the regions, and thus recognize certain signs of architectural distortion which were not available to previous methods. Work on the segmentation of mammograms into fat and non-fat regions have been published previously [2]. The results showed that Laws' texture energy [3] was the most successful segmentation method tested, on average correctly classifying 80% of the breast area in a 40 mammogram data set.

The aim of the segmentation is to extract ROIs containing all masses and locate the suspicious mass candidates from the ROI. Segmentation of the suspicious regions on a mammographic image is designed to have a very high sensitivity and a large number of false positives are acceptable since they are expected to be removed in later stage of the algorithm [4]. Researchers have used several segmentation techniques and their combinations.

Global thresholding [5] is one of the common techniques for image segmentation. It is based on the global information, such as histogram. The fact that masses usually have greater intensity than the surrounding tissue can be used for finding global threshold value. On the histogram, the regions with an abnormality impose extra peaks while a healthy region has only a single peak [6]. After finding a threshold value the regions with abnormalities can be segmented. Global thresholding is not a very good method to identify ROI because masses are often superimposed on the tissue of the same intensity level. Global thresholding has good results when used as a primary step of some other segmentation techniques.

Local thresholding is slightly better than global thresholding. The threshold value is defined locally for each pixel based on the intensity values of its neighbour pixels [6]. Multiple pixels belonging to the same class (pixels at the periphery of the mass and pixels at the center of the mass) are not always homogenous and may be represented by different feature values. Li et al. [7] used local adaptive thresholding to segment mammographic image into parts belonging to same classes and an adaptive clustering to refine the results. Matsubara et al. [8] developed an adaptive thresholding technique that uses histogram analysis to divide mammographic image into three categories based on the density of the tissue ranging from fatty to dense. ROIs containing potential masses are detected using multiple threshold values based on the category of the mammographic image.

Dominguez and Nandi [9] performed segmentation of regions via conversion of images to binary images at multiple threshold levels. For images in the study, with grey values in the range [0, 1], 30 levels with step size of 0.025 were adequate to segment all mammographic images.

Varela et al. [10] segmented suspicious regions using an adaptive threshold level. The images were previously enhanced with an iris filter. Li et al. [11] used adaptive gray-level thresholding to obtain an initial segmentation of suspicious regions followed by a multiresolution Markov random field model-based method.

Markov random field (MRF) or Gibbs random field (GRF) is one of the segmentation methods in iterative pixel classification category. MRFs/GRFs are statistical methods and powerful modeling tools [11]. Székely et al. [12] used MRF in "fine" segmentation to improve the preliminary results provided by the "coarse" segmentation. In "coarse" segmentation the feature vector is calculated and passed to a set of decision trees that classifies the image segment. After the "fine" segmentation they used a combination of three different segmentation methods: a modification of the radial gradient index method, the Bézier histogram method and dual binarization to segment a mass from the image. Region growing and region clustering are also based on pixel classification. In region growing methods pixels are grouped into regions. A seed pixel is chosen as a starting point from which the region iteratively grows and aggregates with neighboring pixels that fulfill a certain homogeneity criterion. Zheng et al. [13] used an adaptive topographic region growth algorithm to define initial boundary contour of the mass region and then applied an active contour algorithm to modify the final mass boundary contour. Region clustering searches the region directly without initial seed pixel [6].

Pappas [14] used a generalization of *K*-means clustering algorithm to separate the pixels into clusters based on their intensity and their relative location. Li et al. [12] used an adaptive clustering to refine the result attained from the localized adaptive thresholding. Sahiner et al. [15] used *K*-means clustering algorithm followed by object selection to detect initial mass shape within the ROI. The ROI is extracted based on the location of the biopsied mass identified by a qualified radiologist. Initial mass shape detection is followed by an active contour segmentation method to refine the boundaries of the segmented mass.

Edge detection algorithms are based on the gray level discontinuities in the image. Basis for edge detection are gradients or derivatives that measure the rate of change in the gray level. Rangayyan [7] described standard operators for edge detection such as Prewitt operator, Sobel operator, Roberts operator and Laplacian of Gaussian (LoG) operator.

Fauci et al. [16] developed an edge-based segmentation algorithm that uses iterative procedure, a ROI Hunter algorithm for selecting ROIs. ROI Hunter algorithm is based on the search of relative intensity maximum inside the square windows that form the mammographic image.

A core biopsy is a procedure where a needle is passed through the skin to take a sample of tissue from a mass or lump. The tissue is then examined under a microscope for any abnormalities. Core biopsy may be performed when a suspicious lump is found, for example a breast lump or enlarged lymph node, or if an abnormality is detected on an imaging test such as x-ray, ultrasound or mammography.

Core biopsy is a more invasive procedure than fine needle aspiration biopsy, however, it is quicker and less invasive than a surgical biopsy. In some cases, the result of a core biopsy will prevent the need for surgery to take place.

If you have a breast lump and want it checked out, a Surgical biopsy is a good way to get a clear diagnosis. This type of breast biopsy removes the largest size of tissue sample, as compared to any type of needle biopsy. In some cases, the entire mass and a margin of healthy tissue may be removed. The tissue will be examined in a pathological lab right away to ensure that it is an accurate sample and get a diagnosis. Surgical breast biopsy takes the largest tissue sample and has the highest accuracy rate of all biopsy methods.

A pathology lab can use two methods to study your tissue sample. The quickest method is called "frozen section" or cry section. The tissue is rapidly frozen and sliced with a special blade into a section thin enough to see through. A permanent section method is a more thorough process, using special chemicals to get more information from the tissue slide.

Digital detection process comes in the picture at that moment. The image of histopathological slide under microscope can be processed through digital image processing to detect cancer accurately. Now it is the question that what is the need of digital detection technique where it can be detect easily by human eye itself. Answer is very simple; in all the cases human-error is one of most important factor, which cannot be eliminated completely, especially when it is detection of cancer, which can cause death of the patient. However, there are many more additional advantages of digital detection method.

Distribution and sharing of the digitally processed images of histopathological slide to remote location is much more easily and less time consuming than send the original one to the experts for opinion.

Preservation of digitally processed images of histopathological slide is much simple for future references. In a study, the Department of Pathology at the University Medical Centre (UMC) Utrecht processes some 300 to 500 histopathological slides per day, nearly 100,000 annually, each of which must be processed, scored, and importantly stored; if patients return to the hospital, their slides may need to be re-examined.

Petrick [17] used Laplacian of Gaussian filter in conjunction with density weighted contrast enhancement (DWCE). DWCE method enhances the structures within the mammographic image to make the edge detection algorithm able to detect the boundaries of the objects. Zou et al. [18] proposed a method that uses gradient vector flow field (GVF) which is a parametric deformable contour model. After the enhancement of mammographic images with adaptive histogram equalization, the GVF field component with the larger entropy is used to generate the ROI.

CONCLUSIONS

It can be very difficult to decide who may have a breast cancer and who may have a non-cancerous breast condition. Advances in computing and telecommunications have resulted in the availability of a range of tools for use in mammography quality assurance and support system. The majority focuses on either enabling mammography to examine and diagnose cases, or providing image archives that serve as reference material. Limited emphasis has been placed on analysing the diagnostic process used by mammography to reach a diagnosis and using this as a resource for improving diagnostic performance.

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