Computer Aided Mammography

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ABSTRACT

This research investigated the state of art of computer aided detection systems for digital mammograms, and evaluated the related techniques in image pre-processing, feature extraction and classification of digital mammograms. Furthermore, this paper explored the further research directions for next generation CAD for mammograms. It was identified that computer-aided detection techniques for masses and microcalcifications have been extensively studied, but the detection techniques for architectural distortion and asymmetry in mammograms still are challenges.

Keywords: digital mammography, CAD, breast cancer

1.0 INTRODUCTION

Breast cancer is the most common cancer for women. X-Ray mammography is an effective way to detect breast cancer. A typical mammogram contain various information that represents tissues, vessels, ducts, chest skin, breast edge, the film, and the X-ray characteristics. The computer aided systems for mammograms can be divided in two categories: computer aided detection system (CADe) and computer aided diagnosis system (CAD). CADe is able to identify the Regions of Suspicion (ROS), but CAD can make a decision whether a ROS is benign or malignant. The general process of CAD for mammograms refers to image pre-processing, defining ROS, extracting features and classifying a ROS into benign, malignant or normal.

In mammograms, clustered micro-calcifications, mass lesions, distortion in breast architecture, and asymmetry between breasts have been proved that those are linked to breast cancer (see Figure 1). The appearances of microcalcifications are small bright arbitrarily shaped regions. The appearances of mass lesions are dense regions of different size and properties, which can further described by circumscribed, speculated or ill-defined. [1, 2]

At present. the detection of microcalcifications is still difficult because of their fuzzy nature, low contrast and low distinguish-ability from the ROS. The sizes of microcalcifications are in the range of 0.1-1.0 mm and the average size is 0.3 mm. The shapes, distributions and sizes of microcalcifications are tremendously various. On the other hand, it is difficult to segment microcalcifications because tissues surround them. [3]

Masses are groups of cell that are clustered together, and they have strong density than the surrounded area. The characteristics of size, homogeneity, position of masses are various [4] Christoyianni et al. pointed out that the main obstacle of mass detection is the great variability of mass appearance with other abnormalities. Asymmetry and architectural distortion are also hard to detect [1]. Therefore, the method for detecting all breast abnormalities still is a challenge [5, 6]. The techniques of detection, classification and annotation can benefit to the research of computer aided mammography.

Various researchers have conducted related research for various types of breast abnormalities for more than two decades. Currently, computer aided detection systems for mammograms for mass or microcalcification have been used in clinical routine, such as ImageChecker and SecondLook. [6]

The research of computer aided mammography continues to be developed. For the mass lesions of breast, [7] presents a tool system in 2006, including imaging segmentation of ROI, extracting ROI characterization "by means of textural features computed from the gray tone spatial dependence matrix (GTSDM), containing second-order spatial statistics information on the pixel gray level intensity", and classify ROI with neural network. In 2008, Pal et al. used 24 kinds of features for four types of window sizes to detect microcalcification, which resulted in computing 87 features for each pixel. [8]

2.0 Analysis of techniques for mammograms

The general architecture of a CAD system includes image pre-processing, definition of region(s) of interest, features extraction and selection, and classification. As a whole, the techniques of computer aided mammography cover image enhancement, segmentation, detection and classification. [6].

2.1 Pre-processing

Image pre-processing is a necessary step to improve the image quality of mammograms. The general methods of image pre-processing can be divided into: denoising, enhancement of structure, and enhancement of contrast. The methods of denoising refer to mean filters, median filters, Laplacian filters and Gaussian filters, the methods of enhancing the edges of image structures include unsharping and wavelet transform, and the method of enhancing image contrast can be histogram equalization.[9]

The pre-processing of digital mammograms refers to the enhancement of mammograms intensity and contrast manipulation, noise reduction, background removal, edges sharpening, filtering, etc. Cheng et al.[10] summarised the three kinds pre-processing techniques for digital mammograms: global histogram modification approach, Local-processing approaches, and multiscale processing approach. Cheng et al. [10] also pointed out the global approach is not suitable for mammograms, local enhancement methods don't lead to the enhancement of objects and multiscale processing approaches is flexible to enhance local features. Table 1 summarise current enhancement techniques for mammograms.

2.2 Segmentation and detection

The segmentation techniques are important to separate suspicious areas of masses or microcalcifications from the background texture. The objective of segmentation of suspicious areas is to get the location and classify suspicious into benign or malignant [3]. The suspicious area of a mass has almost uniform intensity, higher than the surrounding, and a regular shape with various size and fuzzy boundaries [11]. The area growing, edge detection, wavelet, statistical methods, Mathematical morphology, the fractal model, Fuzzy approaches have been applied to segment a ROS in digital mammograms.

As the nature of scatted or clustered microcalcification, a range of segmentation techniques have been developed, such as: area growing, edge detection, wavelet, statistical methods, Mathematical morphology, the fractal model, Fuzzy approaches, have been applied to segment a ROI (area of interest) of microcalcification in digital mammograms. The researchers also developed various segmentation techniques for detecting masses. Some of them are similar to the segmentation techniques for microcalcifications, such as threshold-holding, multiscale analysis, fuzzy technique, MRF, region growing. On the other hand, the nature of masses is different from microcalcification. The suspicious area of a mass has almost uniform intensity, higher than the surrounding, and a regular shape with various size and fuzzy boundaries[11]. Some segmentation techniques have been developed especially for detecting masses, such as Bilateral image subtraction (also called asymmetry approach), template matching and model-based segmentation. Based on the research of [3] and [10], Table 3 summaries current main segmentation techniques in the field of computer aided mammography.

2.3 Feature extraction

Many features have been extracted for the abnormalities of mammograms. For the features extraction of masses, [10] summarised the features into three categories, intensity features, shape features and texture features. [1] mentioned the wavelet, fractal, statistical, and vision-models-based features for detecting masses. On the other hand, [3] summarised the features for detecting microcalcification into individual microcalcification features, statistical texture features, multi-scale texture features and fractal dimension features.

The extraction methods of texture feature play very important role in detecting abnormalities of mammograms because of the nature of mammograms. Texture analysis approaches can be summarised into three broad categories: statistical, model-based, and signal processing techniques [12]. There are four texture modelling methods: statistical methods, geometrical methods, model based methods and signal processing methods [13]. The first-order spatial statistics describe the properties of individual pixel values rather than "the interaction of or co-occurrence of neighbouring pixel values" [13]. The second-order spatial statistics is used to describe "properties of pairs of pixel values" [13].

Some statistical texture analysis methods have been used to detect masses or microcalcifications, such as: Gray level difference statistics (GLDS), SGLD (Spatial Gray Level Dependence Matrix), Gray level difference method (GLDM), Gray level run length method (GLRLM). Gray level co-occurrence (GLCM), also called GLCM (Gray Level co-occurrence matrix), is a second order texture descriptor to describe the relationship between groups of two neighbouring pixels. Gray level difference statistics (GLDS) describe the occurrence of two pixels that have different value and separated. Gray level run length method (GLRLM) describes the number of gray level runs of various lengths. Surrounding region dependence method (SRDM) is based on second order histogram matrix and generated from three windows, and has been used to detect microcalcifications [3]. On the other hand, the techniques of multiscale feature analysis have been widely applied in digital mammograms, such as wavelet, Gabor filter bank and Laplacian of Gaussian filter. The fractal analysis and mathematical morphology also contribute the detection of abnormalities of mammograms. Table 4 shows the feature extraction techniques in digital mammograms.

2.4 Classification

The classification methods for classify suspicious areas of mammograms into benign, malignant or normal tissue. The current classification techniques in digital mammograms are very common and same with the classification methods in other fields, such as neural networks, Bayesian belief network, and K-nearest neighbor.One issue is how to select the extracted features to fit various classifiers. Table 2 shows the common classification techniques and their related features in digital mammograms. [10] pointed out that the LDA and ANN (artificial neural network) work well in classifying masses.

3.0 Discussion

The research of computer aided mammography play significant role to detect the early abnormalities of breast cancer. Although the related researches have been developed for more than two decades, there are still some challenges in segmenting, detecting and classifying masses or microcalcifications. The main reason is that masses or microcalcifications are very small, and vary in size, shape, and appearance. It is very difficult to recognise those abnormalities from the background. Therefore, the most important thing for computer-aided mammograms is how to enhance the features of ROS in the background, how to segment ROS from the background, how to represent ROS, and how to classify ROS. In each area, new and robust algorithms need to be developed.

4.0 Conclusion

The computer aided mammography has been extensively studied. The related research mainly is related to detect and classify masses and microcalcifications. The techniques in the field of computer-aided mammography include pre-processing, segmenting suspicious areas, extracting features of ROS, and classifying ROS into benign, malignant or normal tissue. The different techniques or algorithms has been proposed or extended for digital mammograms. However, the reliable detection of masses or microcalcifications is still a challenge. The research for other abnormalities of breast cancer, such as architectural distortion and asymmetry, has not been developed well. For the future research, the two important topics are how to improve the accuracy and reliability of computer aided mammography for masses and microcalcifications, and how to develop new techniques to detect full abnormalities of breast cancer.

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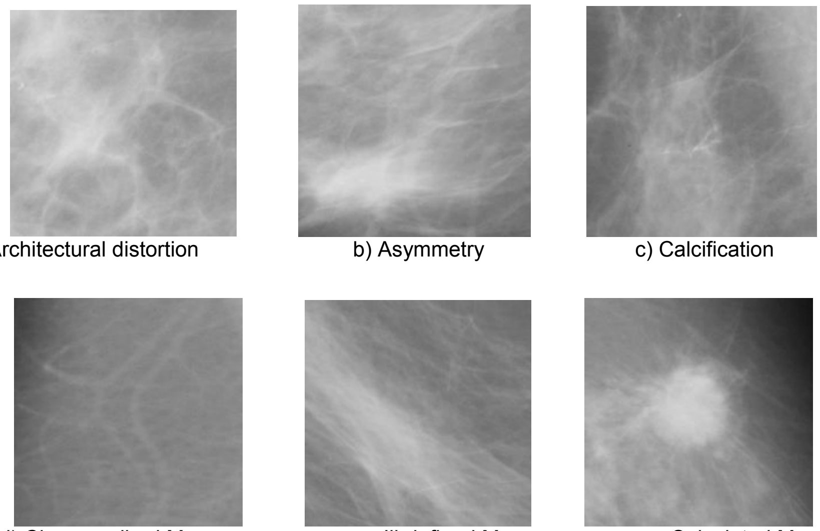

a) Architectural distortion b) Asymmetry c) Calcification

d) Circumscribed Mass Ill-defined Mass Spiculated Mass

Figure 1: Abnormal mammograms are classified into calcification, architectural distortion, asymmetry, circumscribed masses, speculated masses, and ill-defined masses. Source: [2]

Table 1: mammographic enhancement techniques

	Enhancement Methods	Details	Ref.
Global based	Unsharp masking	Remove low frequency information to enhance ROI	[14]
	Adaptive unsharp masking	Use local statistical analysis to enhance ROI	[15]
Region based	Region-based enhancement	Use region growing to enhance ROI	[16]
Local based	Adaptive neighbourhood contrast enhancement (ANCE)	Enhance a small fixed neighbour area	[17]
	Optimal adaptive enhancement	Use local statistical information	[18]
	Contrast-limited adaptive histogram equalization	limit the maximum slope in the transformation function to improve local contrast	[19]
Feature based	Multiscale analysis: dyadic wavelet transform, φ-transform, Hexagonal wavelet transform	Increase the contrast of suspicious areas	[20]
	fractal modelling	remove the background structures and noise from foreground	[21]

Table 2: Classification techniques and features for mammograms

Categories	Details	References
Markov random field models	Statistical classification model using the statistical and contextual information for masses, based on K-means cluster scheme	[22] [4]
ANN	A multi-stage neural network,	[8]
	Radial basis function neural networks (RBFNN) and GLHM, SGLD features	[1] [23] [24]
Pattern matching	Use mass template to check if a area is mass	[25, 26]
Bayesian Belief Network (BBN)	In the "acyclic" graph, each node represents a variable, and merge the extracted features	[3]
K-nearest neighbor (KNN)	co-occurrence features, wavelet features and shape features	[27, 28]
Linear Discriminant Analysis (LDA)	Texture features and morphological features	[10]

Table 3: segmentation techniques for mammograms

categories	Rational	Methods	Ref.
Region growing	Use homogenous gray level information to detect the potential areas	region-growing-based algorithm	[29]
		multi-tolerance region growing	[30]
		Surrounding region dependence	[31]
Statistical analysis	Use statistical analysis to get global and local threshold	Histogram threshold-holding	[32]
	Model spatial relation by maximizing estimation	Markov random field model	[33]
Morphology modeling	Use morphological adaptive threshold to get morphological skeleton information	Top-hat	[34]
	Use the morphological operation, Erosion, to produce skeleton information	Erosion	[35]
	Use morphological filter to generate edge information	Morphological filter	[36]
Multiscale analysis	After transform, use coefficient information to reconstruct images and separate microcalcifications from the background, and various coefficient information represent coarse features and finer features	Multichannel wavelet transform, B-spline function, Multiresolution statistics analysis, Multiscale analysis, Decimated wavelet transform, Undecimated biorthogonal transform, two-stage wavelet transforms, Discrete wavelet transform (DWT)	[37] [38] [39] [40] [41]
Fractal model	Use fractal objects to model images	Fractal model	[21]
Fuzzy approach	Use fuzzy rules and properties to separate	Fuzzy logic	[42]
Information difference	Use the difference of a pair of mammograms to detect ROI of masses	Bilateral image subtraction	[43]
Model-based	Use a range of sizes for the templates to match	Template matching	[11]
	uses a constrained stochastic relaxation algorithm to match	stochastic relaxation	[44]

Table 4: feature extraction techniques for digital mammograms

Feature	Details		Ref
Multiscale feature	Wavelets	Extract the information of Energy, entropy, and homogeneity from various scale images after the discrete wavelet transform, such as Haar and Daubechies 4	[45-48] [49]
	Gabor filter bank	Generate small nonoverlapping blocks after filtered, then extract features	[3]
	Laplacian of Gaussian filter	Transform image into various scale space, then compare Laplacian of Gaussian response of microcalcification	[3]
Fractal feature	fractal dimension measurements (FDM)	Generate fractal dimension of a mammogram Rougher area has great fractal dimension value than smooth area. Fractal dimension is linked to the slope of a plot.	[50] [21]
Statistical texture feature	GLHM (Gray Level Histogram Moments)	mean, variance, skewness and kurtosis	[5]
	GLCM (Gray Level co-occurrence matrix) or SGLD (Spatial Gray Level Dependence Matrix)	14 features: Energy measure, correlation, inertia, entropy, difference moment, inverse difference moment, sum average, sum entropy, difference entropy, sum variance, difference variance, difference average, information measure of correlation, information measure of correlation	[51] [2]
	Surrounding region dependence method (SRDM)	Extract four directional (Horizontal, Vertical, Diagonal, Grid) weighted sum	[52]
	Gray level difference method (GLDM)	4 features: Contrast, Angular second moment, entropy, mean	
	Gray level run length method (GLRLM)	5 features: Short runs emphasis, long runs emphasis, grey-level non-uniformity, run length non-uniformity, run percentage	[52]
Model-based vision	difference-of-Gaussian (DOG) filters	apply difference-of-Gaussian (DOG) filters to detect masses and compute nine features	[53]
morphological features	morphological operations: dilation and erosion	Measure mathematical morphologyof suspicious areas, such as shape	[23]