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Feature Extraction Techniques for Mass Detection in Digital Mammogram (Review)

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Authors' contributions

This work was carried out in collaboration between all authors. Author ATT reviewed the existing works feature extraction techniques (texture based, shape based and intensity based). Author ATM reviewed different works of mass features (descriptors) used by different authors, feature extraction approaches and feature selection. Author SAA drew all the diagrams (the block diagram and the feature extraction diagram). Author OMO reviewed the hybridized features and their accuracy by different authours. Authors OEO and OSO performed the overall review of other authours contributions and made conclusion for the study. All authors read and approved the final manuscript.

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Review Article

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ABSTRACT

One of the most common diseases in women today is breast cancer. The method of detection and analyzing breast images according to literature, to mention few are mammography, magnetic resonance, thermography and ultrasound of which mammography is the most accurate and low

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cost method. Mass is a major symptom of breast abnormality. Despite the high success of mammography in mass detection, radiologists find it difficult to interpret breast abnormality and take decision. Computer Aided Detection (CADe) and Computer Aided Diagnosis (CADx) are the two systems to improve radiologists' accuracy of detection and, classification of breast cancer into benign or malignant prior to biopsy. However, the optimal classification rate of CAD system depends on effectiveness of feature extraction technique. This paper present review of different feature extraction Techniques (FETs) that have been adopted for mass detection and classification.

Keywords: Cancer; feature extraction; breast; mammogram; mass; region of interest; benign; malignant.

1. INTRODUCTION

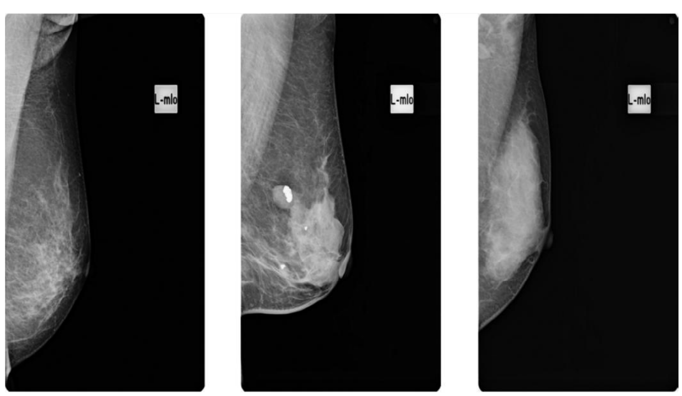
Breast cancer is the prominent cause of highest mortality rate in women [1]. The mortality rates have been reduced due to the implementation of better diagnostic facilities and effective treatments [2]. Early detection of breast cancers often leads to more effective treatment with fewer side effects. However, its early detection is difficult since there are no symptoms at the first stages of breast cancer development [3].

Different imaging techniques such as magnetic resonance, thermography, mammography and ultrasound images are possible for early detection of breast cancer [4]. Mammography is at present, the best available examination for the detection of breast abnormalities [5]. Mammography is a screening and diagnosis techniques for human breast examination or analysis. It makes use of low energy X-rays and a high spatial resolution which makes it efficient to detect subtle fine scale signs [6].

Characterization of masses aids in early detection of breast cancer, typically through detection. Mammographic images have the ability to reveal abnormalities such as masses, calcifications, asymmetries and architectural distortions [7]. Mammograms can be difficult to read due to their low contrast and the differences in the types of breast tissues [8]. The detection of mass is more complicated than micro-calcification because the appearance of the masses are similar to the surrounding parenchyma and they exhibit poor image contrast.

Masses are identified by shape such as round, lobular, irregular and oval. They appear as space occupying lesion. The presents of mass suggest high probability of breast cancer [9]. The result of mass detection can be either benign (non-cancerous cells) or malignant (cancerous cells) [10]. Benign masses have sharp, circumscribed borders where malignant masses have slightly jagged or spiculated borders as displayed in Fig. 1.

Computer Aided Detection (CADe) and Computer Aided Diagnosis (CADx) are the two systems to improve radiologists' accuracy of detection and, classification of breast cancer into benign or malignant prior to biopsy [11].



(a) (b) (c)

Fig. 1. Example of mammogram images with level of abnormal severity (a) normal mammogram (b) benign mammogram (c) malignant mammogram

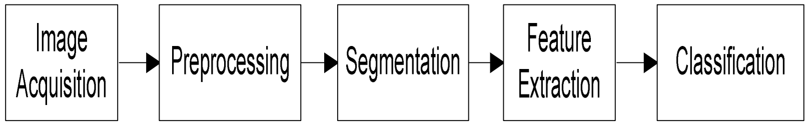


Fig. 2. Block diagram of a CAD system

Most diagnosis algorithms of CAD consist of one stage with four steps: preprocessing, segmentation, feature extraction and classification as presented in Fig. 2. The performance of a CAD system depends more on the methods used in extraction of features than the classification methods. The accuracy of any classification depends on the feature extraction stage that is why choosing the most effective FET is important [12]. In this paper, complete review of FETs for mass detection in digital mammogram is discussed.

2. OVERVIEW

Feature extraction is a method of capturing visual content of an image. The objective of feature extraction process is to represent raw image in its reduced form to facilitate decision making process such as classification [8]. Features extraction methodologies analyze objects and images in order to extract the most important features that represent various classes of the objects and images [13].

In mammographic images, the spatial resolution of x-ray which is in the order of few microns permits the visualization masses but it is necessary to extract features from the mammogram to improve performances of the diagnosis in terms of precision and reliability. In a feature extraction process, a set of features are extracted in order to allow a classifier to distinguish between normal and abnormal pattern. Extracted features are used in neural classifiers to train it for the recognition of particular class either normal or abnormal as demonstrated in Fig. 3 [14].

The ability of the classifier to assign the unknown object to the correct class is dependent on the extracted features [8]. Several features are extracted from digital mammograms including texture features, intensity features and shape features [12]. This paper reviews different approaches that have been developed to address the challenge of extracting features from a mammogram in order to reduce the error of false negatives and false positives.

3. FEATURE EXTRACTION TECHNIQUES (FETS)

3.1 Shape Based FETs

Shape is an important visual feature and it is one of the primitive features of a mass. The irregularity of the Shape of a mass makes it content difficult to extract. Shape extraction techniques can be divided into two main categories: region based and contour-based methods [15]. Region-based methods use the whole area of an object for its shape features, while contour-based methods use only the information present in the contour of an object. Shape features are sometimes categories as a morphological feature.

Tralic, Bozek and Grgic [16] proposed a shape analysis of masses in mammographic images which includes representation of mass contour and shape factors. Three shape factors namely compactness, moments and area descriptors were calculated and used for classification. Eltonsy, Tourassi and Elmaghraby [17] displayed a technique for the automated detection of malignant masses in screening mammography. The technique was based on the presence of concentric layers surrounding a focal area with suspicious morphological characteristics and low relative incidence in the breast region.

A CAD system was developed by Delogu, Fantacci, Kasae and Retico [18] for the classification of mammographic masses as malignant or benign. They used twelve features based on shape, intensity and size of the segmented masses. In the study by Rangayyan, Mudigonda and Desautels [19] combined speculation index, three shape factors, fractional concavity and compactness and achieved classification accuracy of 81.5%. Cascio *et al.*, [20] used geometrical features about shape parameters for each region of interest to classify the masses. They used supervised neural network which achieved a sensitivity value of 82%.

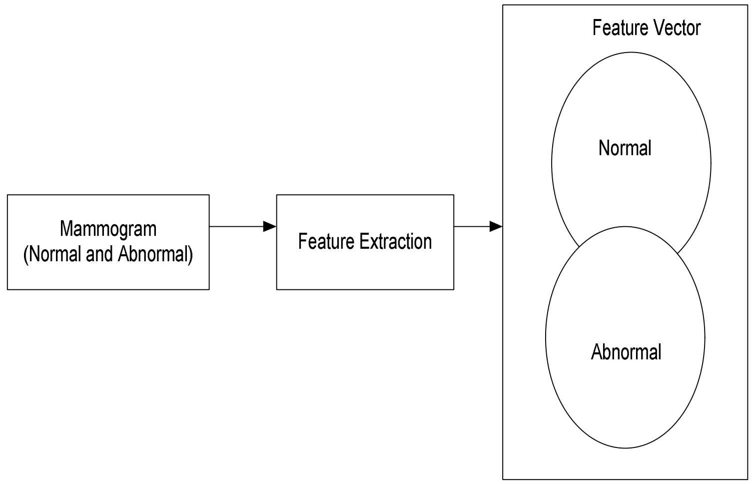


Fig. 3. Simple block diagram of feature extraction

Martins, Silva, De Paiva and Gattass [21] presented a mass detection method that use Growing Neural Gas algorithm to perform the segmentation step. Shape measures were computed in order to discard bad mass candidates. Yang, Dong and Fotouhi [22] present a survey of the existing approaches of shape-based feature extraction, the shape feature extracted was inputted into a classifier and an accuracy of 85% was achieved.

Shape features are important for mass identification because they can distinguish between masses and normal breast using the edges and margin characteristics. Most researches done using shape based feature techniques achieved low accuracies due to the fact that visual features cannot successfully classify masses. The primary advantage of shaped based FETs is that it extracts the spatial arrangement of the pixels which is a very important factor to discriminate masses from normal tissue but not sufficient enough to detected if a mass is cancerous (malignant) or non-cancerous (benign).

3.2 Texture Based FETs

Textures represent tonal variations in the spatial domain and determine the overall visual smoothness or coarseness of image features [7]. They reveal vital information about the structural arrangements of the objects in an image and their relationship to the environment. Texture processing algorithms are usually divided into three major categories: structural, spectral and statistical. Structural methods consider textures as repetitions of basic primitive patterns with a certain placement rule [23].

Spectral methods are based on the use of a different space by a transform. These transforms analyzing the power spectrum, images are oriented at various directions in multiple scales, with flexible aspect ratios and they are helpful to separate a special data [15]. Statistical methods are based on statistical parameters [12]. In mammograms, the characteristics of the pixels in the texture pattern are not similar everywhere. To cope with this specificity, statistical approaches for texture analysis, many techniques have been developed to discriminate different textures in mammographic images [24].

Choi, Kim and Ro [25] proposed the classification of mammograms in breast masses or normal tissue, using multi-resolution Local Binary Pattern classified by SVM-RFE. Ioan and Alexandru [26] used Gabor wavelets to extract texture features at different orientation and frequencies. Dimension of filtered and unfiltered high-dimensional data can be reduced by Principal Component Analysis. Results outperform the radiologist sensitivity reported as being 75%. For the normal versus tumor case, though the specificity is relatively low, a promising value for the sensitivity is achieved.

Shobha [27] proposed texture feature extraction of mammogram images based on Bi-orthogonal wavelet filter via lifting scheme in all bi-orthogonal wavelets, predict and update filter coefficients are also got. These coefficients are adapted later and thus found the optimal wavelet filter bank for increasing the retrieval performance of the retrieval system. By using lifting scheme methodology decomposition of masses were done and thus got approximation and detail coefficients of image.

Texture based FETs provide important discriminatory characteristics related to variability patterns of a digital mammogram [18]. Their analysis is done over a continuous range of scales. They can clearly distinguish between cancerous masses and non-cancerous masses because cancerous masses are stochastic biological phenomena which show in images as various structures occur at different size and over ranges of spatial scales. The characterization of cancerous lesion necessitates the analysis over scales. Although, sharpness and scale of interpretation of boundary vary in masses. The main disadvantage is that if a classifier is used, there are fewer samples for training.

3.3 Intensity Based FETs

Pixel intensities are simplest available feature useful for pattern recognition [5]. According to [14] intensity features of breast images are first order statistics which relies on individual pixel values. The intensity variation in breast images can be measured by median, mode, standard deviation and variance [17]. Kegelmeyer et al. [28] developed the idea of using the local edge orientation histogram feature as a normal mammogram to exhibit a tissue structure that radiates in a particular orientation from the nipple to the chest in regions containing spiculated lesions, edges, which would exist in many different orientations.

Karssemeijer and Brake [29] detected masses by analysis of a map of pixel orientations. The orientation at each pixel was computed from the response of three filter kernels. However, salient contents of region of interest can be missed if the neighbourhood (boundary) is too large or too small. Mudigonda et al. [30] proposed a method for the detection of masses in mammographic images based on the analysis of iso-intensity contour groups.

Sampat, Bovik, Whitman and Markey [31] proposed a new class of linear filters, spiculated lesion fillters, for the detection of converging lines or speculation pixel structures of spiculated masses. Zwiggelaar et al. [32] described a technique to characterize patterns of linear structures using principal component analysis and factor analysis. The primary advantage of intensity based FETs is that, large sampling number of features for each pixel from the local neighborhood of the pixel are extracted to train a classifier. The inherent disadvantage is that, intensity based FETs does not consider the spatial arrangement of the pixels; which is the major factor to differentiate abnormal (mass) from normal tissue.

3.4 Hybridized FETs

This is the combination of two or more feature extraction techniques in order to attain higher truthfulness. This help to improve mass detection by increasing true positive rate and reduce false positive rate thereby creating development in the CAD system. In hybrid FETs, there is always high percentage of accuracy because two or more features were combined as displayed in Table 1.

Table 1. Hybridized features and their accuracies

Year	Author	Type of features used	Accuracy
2010	Aquino, Gegúndez-Arias and Marín [33]	Shape and Intensity	86%
2011	Han, Dong, Guo, Zhang and Wang [34]	Shape, Intensity and Texture	90%
2012	Dash and Sahoo [35]	Intensity and Shape	85.9%
2013	Arymurthy [36]	Texture and Shape	91%
2014	Nugroho, Faisal, Soesanti and Choridah [37]	Intensity and Texture	91.66%
2015	Dhungel, Carneiro and Bradley [38]	Morphological(Shape) and Texture	96.3%
2016	Kanchanamani and Varalakshmi [39]	Texture and Intensity	92.5%

4. MASS FEATURES THAT CAN BE EXTRACTED IN DIGITAL MAMMOGRAMS

Digital mammogram possesses different features, which can be extracted by different techniques. These features are categorized by their properties or by the technique used for its extraction.

4.1 Mass Shape Features

According to BIRADS mass shape characteristics, benign masses tend to have round, oval, lobular in shape. Measuring regular and irregular shapes mathematically is found to be a difficult task, since there is no single measure to differentiate various shapes. The masses are classified into 4 categories such as either round, oval, lobular or irregular [40]. Mass shape features like circularity, thinness ratio, diameter, eccentricity and compactness are used to measure shape characteristics as shown in Table 2.

4.2 Mass Texture Features

Texture features is another type of feature techniques that is highly reliable in aiding classifiers to discriminate normal from abnormal breast tissue. Some of the texture features that can have extracted are demonstrated in Table 3.

4.3 Mass Intensity Features

The intensity and its variation inside a mammographic image can be measured by features like: median, mode, variance, mean value and standard deviation as shown in Table 4.

Features (descriptors) can be refer to as the result of a general neighborhood operation applied to the image or a specific structures in the image itself, ranging from simple structures such as points or edges to more complex structures such as objects [17]. They are computed mathematically, which are not evident to human eye and not easily extracted visually.

Table 2. Shape features

Shape features	Expression	Impact
Area (A)	$\sum_{r=0}^{height-1} \sum_{c=0}^{width-1} I_i(r,c)$	The number of pixels in the mass.
Perimeter (P)	$n_o + \sqrt{2}n_e$	The number of pixels in the boundary of the mass
Compactness (C)	$P^2/4\pi A$	Degree of deviation of the mass from a perfect circle.
Circularity (CIR)	$4\pi A/p^2$	Measures the degree of how circular a certain object is
Complexity (COM)	$10^{-3/n}$	Measures the amount of disorder.

Table 3. Texture features

Texture features	Expression	Impact
Median (M)	$M = \frac{X(n-1)}{2}$ for n odd $M = \frac{1}{2}\left[\frac{X_n}{2} + \frac{X_n}{2} + 1\right]$ for n	Middle value of the mean dataset arranged in ascending order.
Mean	$\overline{X} = \frac{\sum x}{n}$	Average of all the pixels in the segmented ROI.
Variance (σ^2)	$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(i-M)$	Measures the variability of values in the mean dataset.
Standard Deviation (SD)	$SD = \sqrt{\frac{\sum(x-\overline{x})}{n}}$	Describes the dispersion within the ROI
Smoothness (R)	$R = 1 - \frac{1}{1+\sigma^2}$	Measures the level of contrast that can be used to establish descriptor of relative evenness

Table 4. Intensity features

Intensity features	Expression	Impact
Contrast (C)	$C = \sum_{i,j} \lvert i-j \rvert^2 P(i,j)$	Measures the degree of intensity between pixel and its neigbour over the whole image.
Uniformity (U)	$U = \sum_{p=0}^{n-1} P^2$	Measures the similarity or the uniqueness among the pixels
Homogenity (H)	$H = \sum_{i,j} \frac{P(i,j)}{1+\lvert i-j \rvert}$	Measures the closeness of the distribution of elements in the image
Entropy (E)	$E = \sum_{i} P(i/d).\log P(i/d)$	Measure the randomness that can be used to characterize the texture of an image
Energy (e)	$e = \sum_{L=0}^{L-1} [P(i)]^2$	Estimate of the mean square deviation of grey pixel value.

Table 5. Mass features (descriptors) used by different authors

Author (Year)	Features (Descriptors)
Valliappan, Putra and Mandava (2010) [41]	Skewness, Kurtosis, Circularity, Compactness, Contrast, Standard Deviation, Intensity, Area, Length, Breath, Convex Parameter and Roughness
Han, Dong, Guo, Zhang and Wang (2011) [34]	Mean, Standard Deviation, Circularity, Eccentricity, Area, Solidity and Extent
Pradeep, Girisha, Sreepathi And Karibasappa (2012) [42]	Mean, Standard Deviation, Smoothness, Entropy, Skewness, Kurtosis, Root Mean Square, Inverse Difference Moment, Energy, Contrast, Correlation, Homogeneity and Variance
Herwanto and Arymurthy (2013) [43]	Mean, Median Variance, Kurtosis, Skewness, Contrast, Correlation, Energy and Homogeneity
Nandi and Nang (2014) [44]	Contrast, Mean, Entropy, Inverse Difference Moment, Angular Second Moment and Area
Dong et. al., (2015) [45]	Area, Perimeter, circularity, Shape Factor, Length, Mean, Standard deviation, Entropy, Smoothness, Skewness, Uniformity and Kurtosis
Kaur and Singla (2016) [46]	Energy, Contrast, Correlation and Homogeneity

In order to generate feature vectors to be used in the classification stage [24]. Descriptive features (descriptors) are extracted from mammogram directly and are described analytically as used by different authors in classification of mammogram into normal and abnormal as shown in above Table 5.

5. OVERVIEW OF FEATURE SELECTION

In Feature extraction the original set of features is transformed to give a new set of features while Feature selection problem consists in making good predictions with as few variables/features as possible [47]. The main purpose of feature selection is to reduce the number of features used in classification while maintaining acceptable classification accuracy [48]. Finding an optimal feature subset is usually very difficult and many problems related to feature selection have been shown to be non-deterministic polynomial (NP) time hard [49]. Although the reasons for performing feature selection as stated by [50] include: improving performance prediction, reducing computational requirements, reducing data storage requirements, reducing the cost of future measurements and improving data or model understanding but if classifier can get optimal accuracy with the extracted features there may be no need for feature selection after transformation of data since it was stated by [51] that Feature extraction and feature selection are the duo to perform efficient dimensionality reduction. Also, Feature extraction in decomposed in two steps: feature construction, and feature selection according to [52].

Table 6. Feature extraction approaches [53]

Authors	Supervised approach	Unsupervised approach
[54]	Conducted dimensionality reduction blindly (i.e. in an unsupervised manner) adversely affects subsequent classification stage.	
[55]		It is shown that on clinical test data that unsupervised techniques work better than supervised for very high dimensional representations.
[56]		Claims that kernel based unsupervised dimensionality reduction by maximizing information in covariates is preferable to supervised approach for the purpose of clustering and visualization as well as embedding data into very few dimensions.
[57]	supervised learning of nonlinear approximate map parameters instead of random generation, which results in a more compact model and competitive performance	

6. CONCLUSIONS

Early detection of breast cancer cells can be predicted accurately by the use of a precise feature extraction technique. This will help to identify the disease pattern of breast cancer in mammography. This paper reviewed different mass extraction based techniques and features that have been used for the improvement of feature extraction stage in a CAD system. It will help in proper identification of normal and abnormal breast tissue as well as cancerous (benign) and non-cancerous masses (malignant). This review can help reduce false positivity and false negativity in mammogram readings if the right technique is used for mass extraction. It will also assist the radiologist in choosing a helpful method among varieties of FETs.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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