Investigation of multiorientation and multiresolution features for microcalcifications classification in mammograms

Aqilah Baseri Huddin[1], Brian W.-H. Ng[2], Derek Abbott[3]

School of Electrical and Electronic Engineering,
University of Adelaide, SA 5005, Australia
[1] aqilah@eleceng.adelaide.edu.au
[2] bwng@eleceng.adelaide.edu.au
[3] dabott@eleceng.adelaide.edu.au

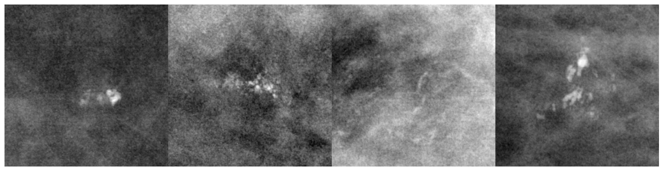
Abstract—**Breast cancer is one of the most common cancers among women. One of the early signs of the disease is the appearance of microcalcifications clusters, which often show up as bright spots in mammograms. It is important to be able to distinguish between the shapes of these clusters to increase the reliability and accuracy of the diagnosis. In this paper, a new method to extract features to classify the microcalcification clusters using steerable pyramid decomposition is presented. The method is motivated by the fact that microcalcification clusters can be of arbitrary sizes and orientations. Thus, it is important to extract the features in all possible orientations to capture most of the distinguishing information for classification. The proposed method shows a clear improvement in the classification performance when compared to the wavelet transform; the most commonly used multiscale analysis technique at present.**

I. Introduction

Based on statistics collected by the World Health Organization (WHO), it was estimated that 460 000 women died from breast cancer in 2008 [1]. Mammography is the main clinical technique that uses low amplitude X-rays to detect early signs of cancer in breast tissue [2]. An early detection of cancerous tissue can help to reduce the number of fatalities and improve the success rate of treatments by 30-70% [3].

After the mammography procedure is made, the radiologist will look up for the anomalies on the film obtained. Some of the conventional signs that radiologist always looked for in mammograms to detect breast cancer are the appearance of cluster of calcifications and poorly defined mass. There are also some of indirect signs that could related to breast cancer such as architectural distortion of breast tissue, asymmetry densities and nipple retractions [4]. However, in this paper, the focus will be in diagnosing the appearance of microcalcifications. Microcalcifications are tiny deposits of calcium that are formed in the breast tissue. Isolated individual microcalcifications are less worrying compared to clusters of microcalcifications. Typical micro-calcifications appear in a group, or are ‘clustered’, in mammograms. Their sizes vary greatly from 10 μm to up to few millimetres and their shapes can also vary from spherical to elongated [5].

However, different shapes of cluster might be associated with different type of diagnosis results, e.g. benign or malignant. A study has reported that only 34% from the total microcalcifications cases involved are actually malignant and required further biopsy [6]. From the pathological perspective, benign cluster are usually smooth and more rounded compared to malignant clusters where each cluster is usually elongated and irregular [7]. Some examples of micro-calcification clusters in mammograms are shown in Fig. 1.



(a) (b) (c) (d)

Fig. 1. (a-b) Benign and (c-d) malignant cluster of microcalcifications on mammograms from the Digital Database for Screening Mammograms DDSM [8].

Due to the low dynamic range and low contrast of film, together with the fuzziness shapes and sizes of microcalcifications, the classifications of microcalcification clusters are often made inaccurately. Classifying micro-calcifications into benign or malignant case accurately could help in reducing number of unnecessary biopsies and unnecessary anxiety in patients. With the advance in imaging technology, Computer Aided-Detection (CADe) and Computer Aided-Diagnosis (CADx) can be used to help radiologists in diagnosing breast cancer. CAD systems, both detection and diagnosis are not aimed to replace the expertise of radiologist but to act as a ‘second opinion’ [5]. The aim of CADe is to detect or identify any suspicious microcalcifications in mammograms. On the other hand, CADx aims to assist radiologists in characterization of the detected microcalcification clusters into benign or malignant classes. Fig.2 shows the schematic of main steps involved in the CADx scheme.

An input to the CADx system is a region of interest (ROI) that contains suspected microcalcifications. This ROI is detected and marked by the radiologist or CADe system. The first step in CADx system is to extract the features of microcalcifications cluster. These features will represent the pattern or characteristic of the class of microcalcifications cluster, benign or malignant. Different types of features can be extracted to classify the cluster. This will be discussed in next section, together with some previous work that has been carried out using a different approach for feature extraction. The extracted features will then be the input to the supervised classifier. Feature selection step is aimed to reduce the number of features to an acceptable number, and thus reduce the complexity of the system. The classifier will learn the pattern of these known samples for both benign and malignant cases. The system now has a supervised training pattern that can be used to classify the unknown sample based on the features extracted.

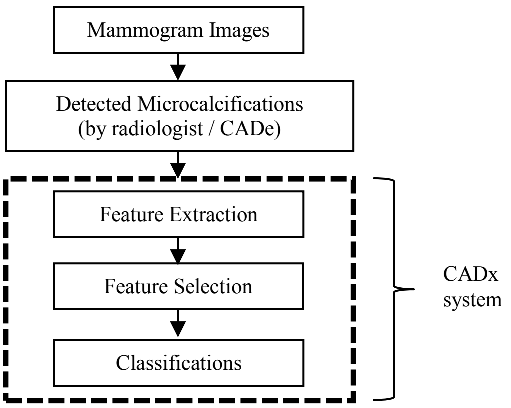


Fig. 2. A flowchart showing the main steps involve in CAD for breast cancer diagnosis in mammograms.

The efficiency of the system can be evaluated based on the accuracy of the system in classifying the cluster. Four possible outcomes of the classifier and its terms are as follows:

- True positive (TP), when the classifier makes a correct hit, the patient has disease
- True negative (TN), when the classifier makes a correct rejection, the patient no disease
- False positive (TP), when the classifier makes an Error Type I, the patient with no disease is diagnosed with disease
- False negative (TN), when the classifier makes an Error Type II, the patient with disease is diagnosed with no disease

These outcomes then can be used as an input to plot a receiving operating characteristic (ROC) curve. This curve is representing the relationship between True Positive Rate (TPR) and False Positive Rate (FPR). It is targeted to have a system with high accuracy or high TPR with a reasonably accepted number of false alarm rates.

In this paper, a new method to extract features to classify the cluster of microcalcifications using steerable pyramid is presented. The method is motivated by the fact that microcalcification clusters can appear in arbitrary orientations and sizes. Thus, it is important to extract features in all possible orientations to get the most discriminate features for classifying the clusters. For each detail image in the steerable pyramid analysis, statistical measures such as energy and entropy are calculated; the values from all detail images are collated to form a feature vector. Due to the large number of detail images produced by the steerable pyramid, the size of the features vectors also increased. To reduce the computational burden, the dimension of the feature vector is reduced using Principal Component Analysis (PCA). Finally, supervised learning classifier is used to learn the pattern of the microcalcifications cluster. The classifier that is used in this paper is the support vector machine (SVM).

II. Related Work

In the past two decades, many approaches in CADx system to differentiate between malignant and benign micro-calcifications have been studied. The important step involved before classifying was done is the extraction of features. It is important to extract the most discriminate features that can be used to classify the malignancy of the microcalcifications.

Different approaches have been studied to classify the cluster of microcalcifications such as classifications by extracting shape-based features and texture-based features. As discussed before, the sensitivity of the classifier is measured by calculating the true positive rate and false positive rate. These rates produce ROC curve where the area under the curve (A_z) can be used to measure the overall performance of the system.

Features of individual microcalcifications are directly extracted from its shape. For example, size, area, compactness, number of microcalcifications and etc. Zadeh *et al.* extract 17 features from each mammogram to characterize the cluster of microcalcifications and obtained the performance of classifier of area under curve of 0.82 [9]. However, this approach required higher accuracy of segmentation of micro-calcifications from the background to assure the robustness of the feature classifications step.

Region-based feature extraction offers an advantage by reducing the demand to have a very accurate segmentation of microcalcifications. This is particularly significant because the microcalcifications are small and subtle and because of the low contrast of mammography, it is possibly to have inaccuracy in segmenting them individually.

Two of the previous approaches that have been used to extract features from microcalcifications using region-based method are statistical texture features and multiscale texture features. Statistical texture features measures the statistical calculations based on the pixel information of the images. One of the methods that can be used to extract the statistical texture features is surrounding region dependence method (SRDM). Lee *et al.* used 4 features that were extracted from the second order histogram matrix and yield an area A_z of 0.73 [10].

On the other hand, multiresolution texture features are extracted from the spatial information of the images. The information was obtained by transforming images into sets of coefficients that contains the information of the images. Multiresolution analysis has shown a great advantage in texture analysis, because of this framework's ability to analyse an image at different resolutions. This is known as 'zooming' property, and has advantage in analysing mammographic images due to the fuzzy shapes and small sizes of microcalcifications. One of the methods that can be used to perform multiscale analysis is wavelet transform. An image is decomposed using wavelet transform into set of detail images at different resolution. Common features that are extracted from these detail images are energy and entropy of coefficients. Dhawan *et al.* used 2 features extracted from multiresolution images as local texture features to discriminate between malignant and benign cases. The images were decomposed using wavelet transform. Together with other global texture features, the performance of the method yields an area under curve of 0.83 [11]. In addition, work by Soltanian-Zedah *et al.* has showed that features extracted from wavelet and multiwavelet gave a good classifier sensitivity compared to the other texture-based features extraction approaches [12].

III. MULTIRESOLUTION ANALYSIS

Previous work has shown that multiresolution analysis of mammographic images has given a promising result in assisting radiologist to identify the class of microcalcifications [12]. Since the sizes and shapes of cluster of microcalcifications are variable, the ability of zooming in multiresolution analysis offers a naturaladvantage in breast cancer diagnosis. Fig. 3 shows a multiresolution analysis that represents an image at different levels.

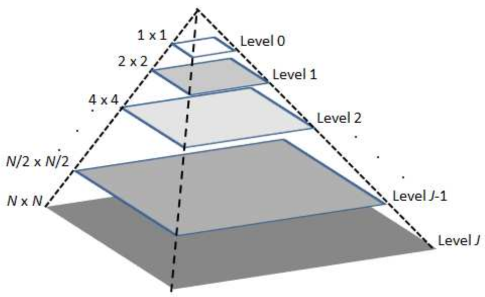
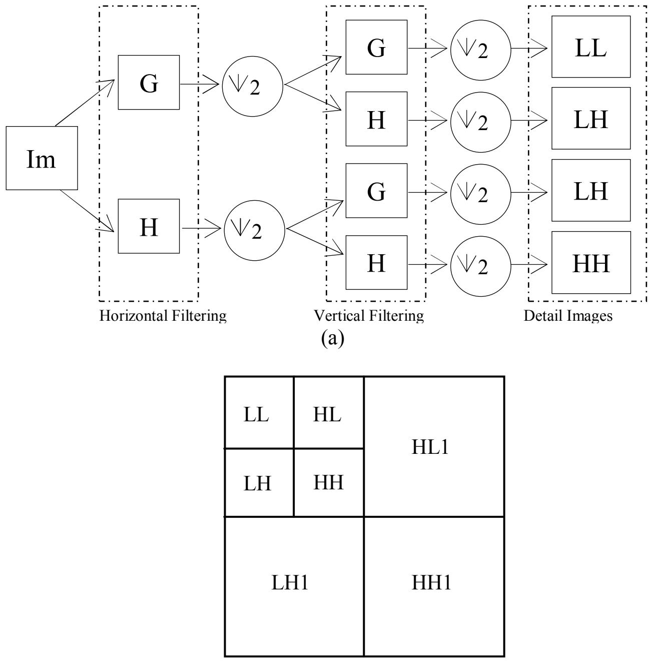


Fig. 3. Multiresolution representation pyramid from coarse to fine resolution

A. Wavelet Features

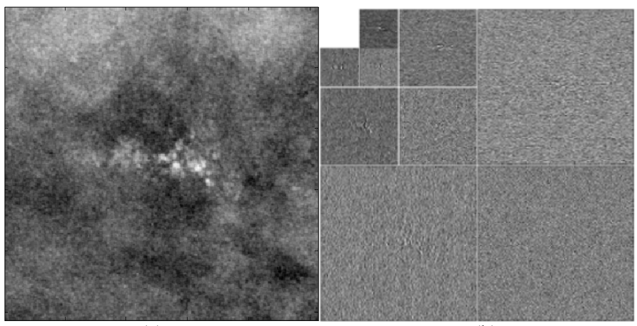
One of the multiresolution analysis tools that has been widely used in image processing is wavelet analysis. Originally proposed in the form of Mallat's pyramidal algorithm, an image can be successfully decomposed into detail sub-bands at different level of resolutions. The decomposition was done by filtering the images using pair of low pass (*G*) and high pass (*H*) filter, followed by downsampling of factor of 2, first along rows and columns. This decomposition is known as 2-dimensional (2D) separable discrete wavelet transform (DWT). Due to the separate row and column processing, this procedure results in 3 detail images at each level: vertical (LH), horizontal (HL) and diagonal (HH) details sub-bands, as shown in Fig. 4 (a). To produce a finer of the decomposed images, the process is then further iterated using approximation images obtained from the previous level. This will result in multiresolution of decomposed images as shown in Fig. 4 (b).

Fig. 5 (b) shows the detailed images of cluster of microcalcifications in Fig. 5 (a) obtained from the decomposition using traditional wavelet transform. The decomposition uses 3 levels of resolution with a factor of 2 between successive levels. Entropy and energy of subimages were used to form 18-dimensional features that represent the image.



(b)

Fig. 4. (a) 2D separable wavelet decomposition (b) Image decomposition at 2 levels of resolution



(a) (b)

Fig. 5 (a) Cluster of microcalcifications (volume: benign_01,case3127) [8] (b) Detail subimages of microcalcifications cluster image from Figure 6 using traditional Daubechies wavelet transform for image decomposition at 3 levels of resolutions

B. Multiorientation and Multiresolution Features

In wavelet decompositions, the orientations of decomposed sub-bands were limited to only 3 directions: horizontal, vertical and diagonal. Another form of multiresolution that has more orientation sensitivity uses a method called steerable pyramid [13]. Fig. 6 shows the decomposition of images using steerable pyramid. The image is decomposed into highpass and lowpass sub-bands using highpass (H) and lowpass filters (L_0). Unlike wavelet transforms, the lowpass sub-band images are then decomposed using a set of bandpass filter (B_k) that can be rotated at different angles, so steerable pyramid produces a set of detail images at arbitrary number of orientations.

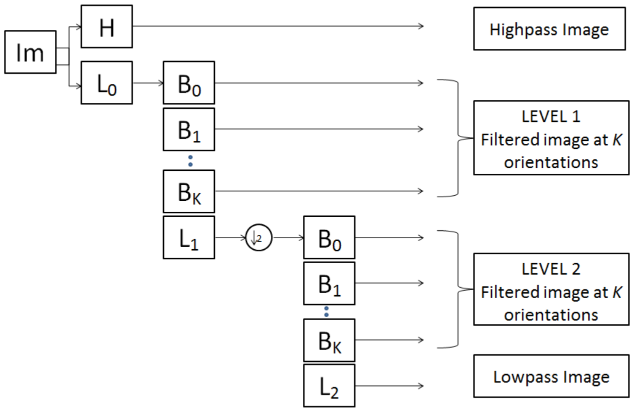


Fig. 6 Image decomposition using steerable pyramids

Fig.7 shows the detailed images of same microcalcifica-tions cluster image in Fig. 5 (a) obtained after the images decomposed using steerable pyramid filters. The pyramid was built using 8 different orientations ranging from 0 to π radians, and 3 different resolutions at factor of 2 between two successive levels. This produces 24-dimensional features to represent an image.

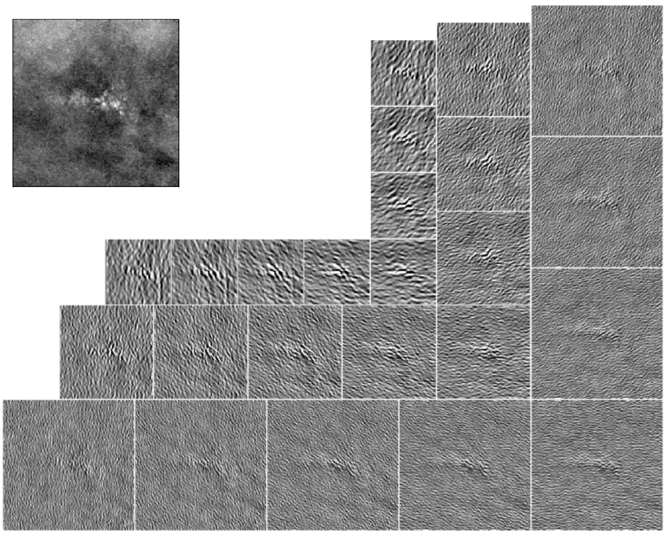


Fig. 7 Detail subimages of microcalcifications cluster (image of microcalcifications at top-left) using steerable pyramid filters for image decomposition at 8 orientations and 3 levels of resolutions

C. Feature vector and Feature Selection

Statistical measures such as energy as in (1) and entropy as in (2) can be used to label a texture. These measures were extracted and calculated from each sub bands to form a feature vector that represent each case of image:

$$Energy = \frac{\sum_i \sum_j x_{ij}^2}{N^2}, \quad (1)$$

$$Entropy = -\frac{\sum_i \sum_j \left[\frac{x_{ij}^2}{norm^2}\right] log_2 \left[\frac{x_{ij}^2}{norm^2}\right]}{log_2 N^2}, \quad (2)$$

where $norm^2 = \sum_i \sum_j x_{ij}^2$, and x_{ij} is the ijth pixel value of detail images.

For selecting best features to represent an image at lower dimension, the technique that we use in this paper is Principal Component Analysis (PCA). PCA is a commonly used technique that can remap a higher dimension of dataset into lower dimensions with minimal effort. PCA calculated the eigenvalues and eigenvectors of the features covariance matrix. Projections onto the eigenvectors corresponding to higher eigenvalues usually yield the most discriminant features.

D. Classifier

Previous work has shown that SVM has outperformed other classifiers such as Neural Network (NN) in classifying microcalcifications [14]. SVM is one of the supervised learning classifier. It is based on maximises the margin between two classes.

IV. Result and Discussion

A. Mammogram Database

Images used in the experiment are collected from the Digital Database of Screening Mammography (DDSM) [8]. The database is available online. It contains a large number of 2620 cases including normal, cancer and benign cases. In this paper, only a subset of 118 microcalcification clusters was used. This is because the purpose of this experiment is as a preliminary investigation into the use of multiorientation feature extraction for microcalcification classification. The images used in this research are all chosen to contain of microcalcifications, but correspond to both cancer (52) and benign (66) cases. Regions of interest (ROI) with size 256 x 256 were cropped according to the chaincode given with the image database, which was marked by the expert radiologist as 'ground truth'.

B. Result

1) Feature extractions

Statistical measures (energy and entropy) for each sub-band in both wavelet and steerable pyramid decompositions were calculated. 3 levels of wavelet decomposition produced feature vectors of length of 9 for each statistical measure, while 3 levels of steerable pyramid analysis at 8 different orientations produced a feature vector of 24 for each statistical measure.

PCA was applied both to statistical measures. Energy and entropy of wavelet transform showed 2 significant eigenvalues, whereas for steerable pyramid decomposition, energy produced 5 significant eigenvalues and 3 significant eigenvalues for entropy. Fig. 8 shows the plot for eigenvalues for each case. We chose the minimum number of significant eigenvalues that is 2, to reduce the dimension of both wavelet and steerable pyramid features vector. This is to give a same set of features vectors sizes to be input in classifications processes.

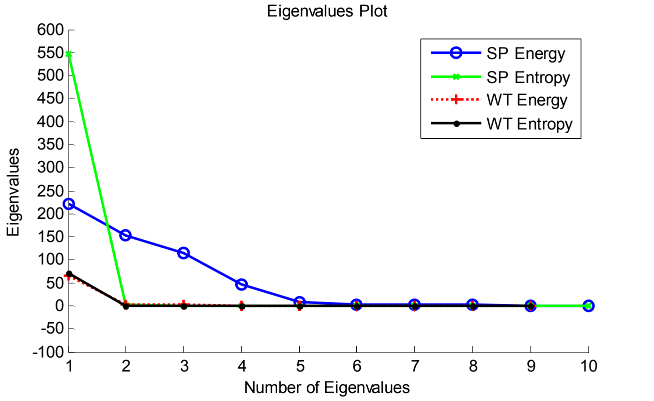


Fig. 8. Eigenvalues plot obtained from PCA method for both energy and entropy from Steerable Pyramid (SP) and Wavelet Transform (WT). Result shows that the number of significant eigenvalues is for energy obtained from steerable pyramid analysis is 5, whilst the other 3 features (entropy from steerable pyramid, energy and entropy from wavelet transform) have at most 2 significant eigenvalues.

2) *Classifications*

Classifications of microcalcifications into benign and malignant is made using SVM with radial basis function (RBF) kernel. There were 2 parameters that needed to be set using this function, which are the penalty parameter C and γ. A grid-search with 5-fold cross validation technique is used to find the best set of these parameters. In 5-fold cross validation method, the dataset are equally divided into 5 sub datasets. One of the sub dataset was used as testing set on remaining sub datasets as training set. A pair of parameters C and γ are used by grid search in the classifier to find the average of percentage that accurately classifies the class of microcalcifications cluster. The pair of parameters that achieved the highest accuracy rates is then used for the SVM throughout this paper.

After the parameters were identified, 50 runs of experiments with 80 training datasets and 38 testing datasets were done. The training dataset and testing dataset with equal number of cancer and benign for each run are randomly chosen in each experiment run. Because of SVM classifier is a binary classifier that produces only a dot in ROC space, the result is made based on the average of TPR and FPR on 50 runs with dataset randomly chosen.

The results obtained from the experiments showed that the classifications using features extracted from steerable pyramid analysis outperform the features extracted from detail images obtained from conventional wavelet decomposition. Table I shows that steerable pyramid features showed true positive rate of 86.2.7% with false positive rate of 0.51. Whereas wavelet features give true positive rate of 77.9% with false positive rate of 0.58. It is observed that the proposed method for features extraction showed better performance compared to the multiresolution features extracted using wavelets.

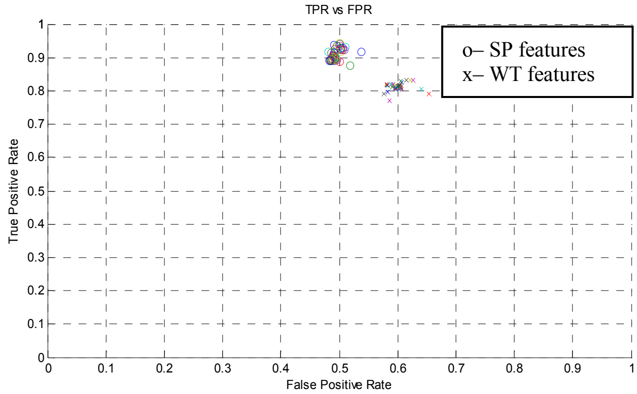


Fig. 9. TPR vs FPR plot for both steerable pyramid and wavelet transform when using entropy as the single feature for classifications. Steerable pyramid shows an average of TPR of 88.9% which outperform the average TPR for wavelet transform, 79.7%

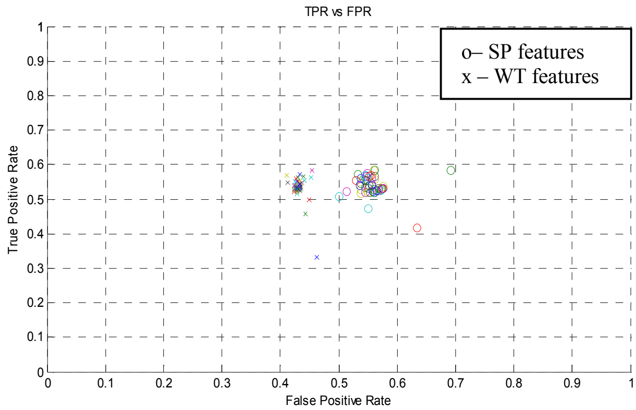


Fig. 10. TPR vs FPR plot for both steerable pyramid and wavelet transform when using energy as the single feature for classifications. Steerable pyramid and wavelet transform shows an almost equal average of TPR of 52.4%. However, the FPR obtained from wavelet transform shows an improvement ~10% over steerable pyramid.

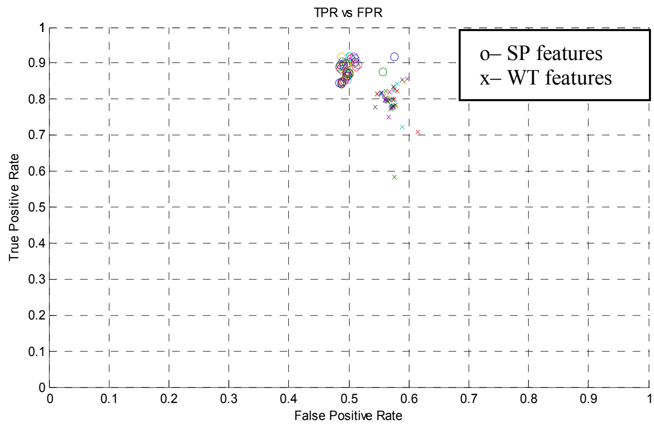


Fig. 11. TPR vs FPR plot for both steerable pyramid and wavelet transform when concatenating both features – Energy and Entropy for classifications. Steerable pyramid shows a good result of accuracy, average TPR of 86.2% compared to wavelet transform which only yield an average TPR of 77..9%. The improvement of 10% in accuracy clearly shows steerable pyramid has a distinct advantage in extracting features for microcalcifications classifications.

TABLE 1

AVERAGE OF TRUE POSITIVE RATE, FALSE POSITIVE RATE AND VARIANCE OF SVM CLASSIFIER WITH 4 REDUCED STATISTICAL FEATURES (2 ENERGY AND 2 ENTROPY)

	Average TPR	Average FPR	Variance
Wavelet Transform	0.7796	0..5790	0.0153
Steerable Pyramid	0.8624	0.5089	0.0134

V. CONCLUSION

This paper proposes a novel method to classify microcalcifications into benign and malignant cases using multiorentation and multiresolution representations. The representation is performed by steerable pyramid filtering of the images. The advantage of this method over wavelet transform is the ability to capture the multiorientation features of microcalcifications cluster. 118 samples of microcalcifications cluster obtained from DDSM database was used in this paper. The supervised learning classifier, SVM with RBF kernel has been used to classify the cluster and the performance was evaluated by the rate of true positive obtained. The performance was compared with the conventional multiresolution representation, wavelet transform. The performance of the proposed method has showed better result compare to the wavelet method. This described the potential contribution of feature extraction via steerable pyramid analysis in microcalcifications classifications.

In future work, the result of the proposed method can be further validated by implementing a controlled study where experts are to involve in identifying the class of the microcalcifications clusters. The results obtain from the proposed method will then compared with the results obtained from the experts to see the real contributions. This controlled study is not implemented in this paper due to the time and resources constraints.

VI. ACKNOWLEDGMENT

The authors would like to thank Simoncelli et al. for providing pyramid algorithm matlab toolbox. Also, the authors would like to express their thanks to the anonymous reviewer for the insightful comments received.

REFERENCES

[1] ["WHO Cancer Fact Sheet. Internet: http://www.who.int/mediacentre/factsheets/fs297/en/index.html," 2011 [Aug. 16, 2011].

[2] "The radiology information resource for patients : Mammography. Internet: http://www.radiologyinfo.org/en/info.cfm?pg=mammo," 2010 [Aug. 11, 2011].

[3] R. M. Rangayyan, F. J. Ayres, and J. E. Leo Desautels, "A review of computer-aided diagnosis of breast cancer: Toward the detection of subtle signs," Journal of the Franklin Institute, vol. 344, pp. 312-348.

[4] E. A. Sickles, "Mammographic features of "early" breast cancer," American Journal of Roentgenology, vol. 143, pp. 461-464, 1984.

[5] R. M. Nishikawa, "Detection of Microcalcifications," in Image-Processing techniques for tumor detection, R. N. Strickland, Ed.: CRC, 2002.

[6] A. M. Knutzen and J. J. Gisvold, "Likelihood of malignant disease for various categories of mammographically detected, nonpalpable breast lesions," Mayo Clin Proc, vol. 68, pp. 454-60, May 1993.

[7] G. M. Tse, P. H. Tan, A. L. M. Pang, A. P. Y. Tang, and H. S. Cheung, "Calcification in breast lesions: pathologists' perspective," Journal of Clinical Pathology, vol. 61, pp. 145-151, Feb 2008.

[8] M. Heath, K. Bowyer, D. Kopans, R. Moore, and W. P. Kegelmeyer, "The Digital Database for Screening Mammography," in Proceedings of the Fifth International Workshop on Digital Mammography, M.J. Yaffe, ed., 212-218: Medical Physics Publishing, 2001.

[9] H. Soltanian-Zadeh, S. Pourabdollah-Nezhad, and F. Rafiee-Rad, "Shape-based and texture-based feature extraction for classification of microcalcifications in mammograms," Medical Imaging: 2001: Image Processing, Pts 1-3, vol. 2, pp. 301-310, 2001.

[10] C. S. Lee, J. K. Kim, and H. W. Park, "Computer-aided diagnostic system for breast cancer by detecting microcalcifications," Image Display - Medical Imaging 1998, vol. 3335, pp. 615-626, 1998.

[11] A. P. Dhawan, Y. Chitre, and C. Kaiser-Bonasso, "Analysis of mammographic microcalcifications using gray-level image structure features," Medical Imaging, IEEE Transactions on, vol. 15, pp. 246-259, 1996.

[12] H. Soltanian-Zadeh, F. Rafiee-Rad, and S. Pourabdollah-Nejad D, "Comparison of multiwavelet, wavelet, Haralick, and shape features for microcalcification classification in mammograms," Pattern Recognition, vol. 37, pp. 1973-1986, 2004.

[13] E. P. Simoncelli and W. T. Freeman, "The steerable pyramid: A flexible architecture for multi-scale derivative computation," Proceeding IEEE International Conference on Image Processing, pp. 444-447, 1995.

[14] L. Y. Wei, Y. Y. Yang, R. M. Nishikawa, and Y. L. Jiang, "A study on several machine-learning methods for classification of malignant and benign clustered microcalcifications," IEEE Transactions on Medical Imaging, vol. 24, pp. 371-380, Mar 2005.