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COMPARATIVE STUDY OF WAVELET DE-NOISING THRESHOLD FILTERS FOR MAMMOGRAM IMAGES CLASSIFICATION BASED ON FUZZY SOFT SET THEORY

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ABSTRACT

Noise present in the digital mammograms directly influences the capability and competence of a classification task which makes de-noising a challenging problem. In the literature, few wavelets like daubechies db3 and haar have been used for de-noising medical images. Nevertheless, wavelet filters such as sym8, dB3, dB4, haar and Coif1 at certain level of soft and hard threshold functions have not been taken into account for mammogram images. Therefore, in this study two wavelet filters namely: sym8 and daubechies db3 at certain level of soft and hard threshold functions have been considered for classification of mammogram images. Meanwhile, in terms of mammogram images classification using data mining methods review on literature showed that no work has been done using fuzzy soft set based similarity measure for classification of mammogram images. Therefore, the positive reviews produced from past works on fuzzy soft set based classification have resulted in an attempt to use fuzzy soft set for mammogram images classification. Thus, the proposed methodology involved five steps namely MIAS dataset, images de-noising using wavelet hard and soft thresholding, region of interest identification feature extraction and classification. Hundred and twelve images (68 benign images and 51 malignant images) were used for experimental set ups. Experimental results show better classification accuracy in the presence/absence of noise in mammogram images where the highest classification rate occurs with db3 (level 4) with accuracy 62.12 % (soft threshold) with CPU time 0.0026sec and classification rate without noise 63.64%.

Keywords: mammogram images, feature extraction, wavelet filters, fuzzy soft set.

INTRODUCTION

Digital mammograms have improved the capability to detect breast abnormalities. In contrast, it has been reported that between 10%-30% of breast cancer are missed by radiologist during routine screening (Mohanty *et al.* 2011). Therefore, several researchers exploring the possibilities of using data mining techniques to diagnose and prognosis the breast cancer using automatic image classification systems (Rangayyan, Ayres and Leo Desautels, 2007; Singh, Mohapatra and Kanungo, 2011). However, quality and accuracy of such automatic image classification systems have been affected by noisy components such as low contrast resolutions, film noise, artifacts etc. Study reveals that overall accuracy of classification systems decrease significantly with increase in noise and decrease can become as significant as 21%. This noise can be added due to several factors such as data acquisition and image preprocessing stage. Therefore, the main purpose of de-noising is to remove noisy components (low contrast resolutions, film noise, artifacts) while preserving the important signal as much as possible. De-noising is often done before the images are to be analyzed. Consequently, de-noising plays a very important role in image segmentation, feature extraction and in the classification task (Naveed *et al.* 2012).

In general, noise filters can be divided into two types, linear methods and non-linear filtering methods. Linear methods involved methods like median, weiner, adaptive and mean filters. Non–linear filtering methods include wavelet transform, multiwavelets and curvelet transform.

Al Jumah *et al.* (2013) worked with various non-linear thresholding techniques such as hard, soft, universal, modified universal and multivariate thresholding in multiwavelet transform domain such as Discrete Multiwavelet Transform Symmetric Asymmetric (SA4), Chui Lian (CL), and Bi-Hermite Bih52S) for different Multiwavelets at different levels to denoised an image and determine the best one out of it. It is found that CL Multiwavelet transform in combination with modified universal thresholding has given best results.

Moreover, in the study of Ramani *et al.* (2013), different filters such as median, weiner, adaptive median and mean filters were used in order to remove noise from mammogram images. From their reported results, adaptive median filter performed well then the others filter. The mean square error (MSE) value was small for adaptive median filter 8.4131(mdb 001) and peak signal-to-noise ratio (PSNR) was reported as 38.8812 db (mdb 001).

Saha *et al.* (2015) de-noised mammogram images by investigating the role of the embedded thresholding algorithm. Wavelet and curvelet transform were used using soft, hard and block thresholding techniques and compared the performance of the thresholding techniques along with the transforms. Hard threshold using either the transforms performs better over all other techniques from poisson noise removal of mammograms.

So far, few wavelet filters like daubechies db3 and haar have been used for de-noising of medical images (Sidh, Khaira and Virk, 2012). Sidh *et al.* (2012) summarizes two wavelet filters namely harr and db3 with additive speckle noise. The findings suggested that db3 wavelet is more efficient as compare to haar filter. De-noising was performed with different medical images such as MRI, ultrasound, CT-scan and x-ray images. The imposed noise was speckle noise with noise level σ =0.1. The best PSNR value occurs with dataset MRI images with 39.1906 db (hard threshold) and 40.5521 db with soft threshold. Malar *et al.* (2013) de-noised mammogram images with three mathematical transform namely wavelet, curvelet and contourlet by hard thresholding.

Likewise, in the work of Lashari, Ibrahim, and Senan (2015), applied VisuShrink hard and soft threshold functions (using universal threshold function) with different wavelet filters to de-noise mammogram images. The purpose of study was to observe the viability of wavelet filters for mammogram images. The highest PSNR for db3 filter was 48.7914 db (hard threshold) and 47.89294 for soft threshold function. The experimental results are also helpful to select the best wavelet transform for the de-noising of particular medical images such as mammogram images.

Thus, the paper provides an alternative de-noising filter for mammogram images. Moreover, it was found that hard threshold is more suitable for mammogram images since images edges were kept and noise was almost suppressed.

Meanwhile, in one of the attempts, soft set theory has been shown to be capable of handling real world problems related to classification in particular texture classification, musical instrument classification and decision making problems. For example, Mushrif and Ray (2006), presented a novel method for classification of natural textures using the notions of soft set theory, all features on the natural textures consist of a numeric (real) data type, have a value between $[0,1]$ and the algorithm used to classify the natural texture is very similar to the algorithm used by Roy and Maji (2007) in the decision making problems.

Later, Lashari and Ibrahim (2013) proposed a framework for medical images based on soft set theory. Subsequently, in their work Lashari and Ibrahim, (2015) performance of two selected classification algorithms based on fuzzy soft set for classification for medical data (numerical data) were evaluated. All dataset were acquired from UCI machine learning repository. The acquired results shows that both approaches based on fuzzy soft set performed well, obtaining a classification accuracy reaching 90% for both classification algorithms. Moreover, the experiments conducted demonstrated the effectiveness of fuzzy soft set for medical data categorization. However, to the best of our knowledge, fuzzy soft set is not yet applied in this image classification domain particularly for mammogram images. Therefore, to conduct this study, the proposed methodology involved five phases as stated in Figure 1.

The rest of the paper as follows: Wavelet thresholding de-noising, hard and soft threshold functions are presented in Section 2. The proposed methodology is given in Section 3, experimental results and discussion is reported in Section 4 respectively. Finally, the overall conclusions of this study are presented in Section 5.

WAVELET THRESHOLDING DE-NOISING

Wavelet thresholding de-noising is based on the idea that the energy of the signal to be defined concentrates on some wavelet coefficients, while the energy of noise spreads throughout all wavelet coefficients. Wavelet threshold de-noising is a very efficient method, the purpose of which is to remove identically distributed gaussian noise (Zang, Wang and Zheng, 2009).

Moreover, de-noising plays a very important role in the field of the medical image pre-processing. It is often done before the image is to be analyzed. The noise present in the images may appear as additive or multiplicative components and the main purpose of de-noising is to remove these noisy components while preserving the important signal as much as possible (Rangarajan, Venkataramanan and Shah, 2002).

Therefore, de-noising is mainly used to remove noise that is present and retains the significant information, regardless of the frequency contents of the signal. In this process much attention is kept on how well the edges are preserved and how much of noise granularity has been removed. Thus, the main purpose of image de-noising algorithm is to eliminate the unwanted noise level while preserving the important features of an image.

Let $x(t) = \{x1(t), x2(t)........,xn(t)\}$ be the signal series acquired by means of a senor. This signal series consists of impulses and noise. $x(t)$ can be expressed as follows (Zang, Wang and Zheng, 2009).

$$x(t) = p(t) + n(t) \tag{1}$$

Where $p(t) = \{p1(t), p2(t)........,pn(t)\}$ indicates identically distributed and in depended Gaussian noise with mean zero and standard deviation σ . The wavelet threshold de-nosing producer has following steps:

1. Transform signal $x(t)$ to the time-scale plane by means of a wavelet transform. It is possible to acquire the results of the wavelet coefficients on different scales.
2. Assess the threshold λ and in accordance with the establish rules , shrink the wavelets coefficients
3. Use the shrunken coefficients to carry out the inverse wavelet transform. The series recovers is the estimation of impulse $p(t)$

The second step has a great impact upon the effectiveness of the procedure. According to Donoho (1995), the universal threshold rule should be applied in the second step. According to him, the universal threshold is defined as follows (Donoho, 1995; Donoho *et al.* 1995).

$$\lambda = \sigma\sqrt{2InN} \tag{2}$$

Where, σ refers to the standard deviation of the noise whereas N refers to the number of data samples in the measured signal.

Thresholding

Thresholding is one of important steps to remove noise. Thresholding is used to segment an image by setting all pixels whose intensity values are above a threshold to a foreground value and all the remaining pixels to a background value (Zang, Wang and Zheng, 2009). Thresholding is mainly divided into two categories: hard thresholding and soft thresholding.

Hard thresholding

The hard-thresholding function used by (Donoho, 1995; Zang, Wang and Zheng, 2009) stated in equation 3

$$\tilde{w}_{j,k} = \begin{cases} \tilde{w}_{j,k} & |w_{j,k}| \geq \lambda \\ 0 & |w_{j,k}| < \lambda \end{cases} \tag{3}$$

It is called keep or kill, keep the elements whose absolute value is greater than the threshold. Set the elements lower than the threshold to zero, where $\tilde{w}_{j,k}$ the signal is, λ is the threshold.

Soft thresholding

The soft thresholding function used by Donoho Donoho(1995; Zang, Wang and Zheng, 2009) stated in equation 4.

$$\tilde{w}_{j,k} = \begin{cases} \operatorname{sgn}(w_{j,k})(|w_{j,k}| - \lambda) & |w_{j,k}| \geq \lambda \\ 0 & |w_{j,k}| \geq \lambda \end{cases} \tag{4}$$

It is called shrink or kill which is an extension of hard thresholding, first setting the elements whose absolute values are lower than the threshold to zero and then shrinking the other coefficients where $\operatorname{sgn}(*)$ is symbol function:

$$\operatorname{sgn}(n) = \begin{cases} 1 & n > 0 \\ -1 & n < 0 \end{cases} \tag{5}$$

MODELING PROCESS FOR MAMMOGRAM IMAGES

The modeling process of this study is depicted in Figure-1, which comprises of five steps namely MIAS (Mammographic Image Analysis Society) dataset, images de-noising using wavelet hard and soft threshold, region of interest identification (ROI), feature extraction and classification. The purpose ROI step is to focal point the process exclusively on the appropriate breast region, which reduces the possibility for erroneous classification. Six statistical features have been extracted as listed in Table-1 and for classification an algorithm have been applied with few modifications in training and testing phase as stated in Section Fuzzy Soft Similarity Set based classification.

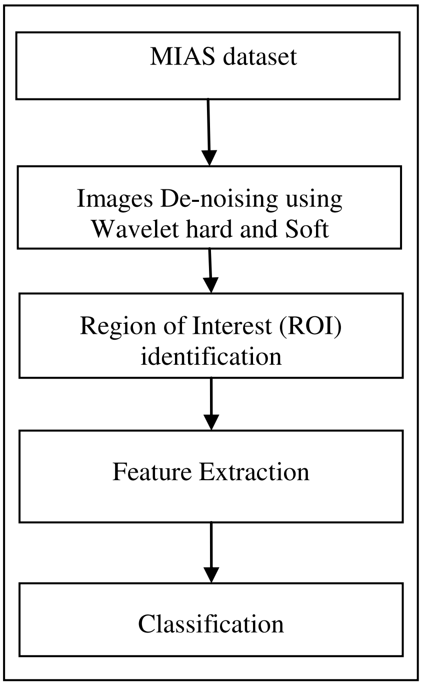

Figure-1. Modeling process for mammogram images.

The statistical features which are mean, variance, skewness, kurtosis, contrast and smoothness are extracted from ROI of the mammogram images (Aarthi, Divya and Kavitha, 2011). The mathematical model to compute the six statistical fealties of a mammogram image are listed in Table-1.

ARPN Journal of Engineering and Applied Sciences

Table-1. Statistical feactures.

Feature	Formula	Description
Mean	$\sum_{i=0}^{L-1} z_i * p(z_i)$	A measure of average intensity
Variance	$\sum_{i=0}^{L-1} (z_i - m)^2 * p(z_i)$	Second moment about the mean
Skewness	$\sum_{i=0}^{L-1} (z_i - m)^3 * p(z_i)$	Third moment about the mean
Kurtosis	$\sum_{i=0}^{L-1} (z_i - m)^4 * p(z_i)$	Fourth moment about the mean
Contrast	$\sum_{i=0}^{L-1} \sqrt{(z_i - m)^2 * p(z_i)}$	Standard deviation of pixel intensities
Smoothnes	$1 - \frac{1}{\left(1+\sigma^2\right)}$	Measures the relative intensity variations in a region

where

$z_i \rightarrow$ is a random variable indicating intensity

$p(z_i) \rightarrow$ is the historgram of the intensity levels in a region

$L \rightarrow$ is a number of possible intensity levels

$\sigma \rightarrow$ is the standard deviation

Fuzzy soft set similarity based classification

As described in the work of Handaga and Deris (2011), the classifier uses similarity between two fuzzy soft sets to classify numerical data. However, in this paper, to classify mammogram images with similarity approach on fuzzy soft set classifier, several lines have been added, such as the second step in training and classification phase, the wavelet de-noising with hard and soft threshold functions using equations 3, 4 and 5.

Fuzzy soft based classifier learns by calculating the average value of each parameter (attribute or feature) from all object or instant with the same class label, to construct fuzzy soft set model with universe consisting of all of class labels. In other words, an object in the universe represents all data derived from the same class label. Furthermore, to classify the test data with unknown class labels, first, construct the fuzzy soft set model of data using formula as stated in equation 7, and then find similarity between two fuzzy soft sets as described in the work of Majumdar and Samanta, (2010) as stated in equation 9.The last is to calculate the class similarity score to determine the class label as stated in equation 10.

Feature fuzzification can be done by dividing each attributes value with the largest value at each attributes (Handaga and Deris, 2011)

$$e_{fi} = \frac{e_i}{\max(e_i)} \tag{6}$$

where $e_i, i = 1,2,.....n$ is the old attribute and e_{fi} is attribute with new value between $[0,1]$.

Classification algorithm

Classification algorithm is divided into two phases namely training phase and classification phase. The description on both phases is given below:

Training phase

1. Given N samples obtained from the data class w.
2. De-noised images using wavelet hard and soft threshold functions using equation 3,4 and 5 and obtain a feature vector E_{wi}, for i=1,2, …, N.
3. Feature fuzzification to obtain a feature vector E_{wi}, for i=1,2, …, N for all training data using equation 6
4. Calculate the cluster center vector $E_w \quad i = 1,2,..,N$.

$$E_w = \frac{1}{N} \sum_{i=1}^{N} E_{wi} \tag{7}$$

5. Obtain fuzzy soft set model (F, E) for class (F, E), is a cluster vector for class w having D features
6. Repeat the process for all W classes.

Classification phase

1. Obtain the unknown class data.
2. De-noised images using hard and soft threshold functions using equations 3,4 and 5 and obtain a feature vector E_{wi}, for i=1,2, …, N
3. Feature fuzzification to obtain a feature vector E_{wi}, for i=1,2, …, N for all testing data using equation 6
4. Obtain a fuzzy soft set model for unknown class data $(\tilde{G}, E)$

ARPN Journal of Engineering and Applied Sciences

5. Compute similarity between $(\tilde{G}, E)$ and $(\tilde{F}, E)$ for each w using equation 9

$$S(F_\rho, G_\delta) = M_i(\tilde{F}, \tilde{G}) = 1 - \frac{\sum_{j=1}^{n} \left|\tilde{F}_{ij} - \tilde{G}_{ij}\right|}{\sum_{j=1}^{n} \left(\tilde{F}_{ij} + \tilde{G}_{ij}\right)} \quad (8)$$

6. Assign the unknown data to class w if similarity is maximum $w = \arg\left[\max_{w=1}^{W} S(\tilde{F}, \tilde{G})\right]$ (9)

where

E_w is mean of feature vectors in the same class label.

g_{wd}, where $w = 1,2,..,W$ and $d = 1,2,..,D$. In this way, a row g_{wd} is a cluster centre vector for every class w having D features.

RESULTS AND DISCUSSIONS

De-noising helps to enhance the content of mammogram images and increases the quality of images and afterward contributes towards better classification accuracy rate. Table-2 depicts different filters with obtained peak signal-to-noise ratio (PSNR) values for hard and soft threshold functions. From the observations, db3 provides better results while compared with the other filters for purpose of de-noising for mammogram images. The best PSNR value is 46.44656db (hard thresholding) and 43.80779 db (soft thresholding). To sum up pre-processing through five wavelet filters, db3 wavelet filter with noise level σ =10 is more suitable for mammogram images. On other hand, mammogram images have good PSNR values; it could be basis that these images high fine detail edges that is why hard thresholding produces enhanced results then soft thresholding.

Table-2. PSNR values for MIAS after processing through different wavelet filters.

	Types of threshold	Filter Sym8	Filter Db3	Filter Db4	Filter haar	Filter Coif1
Mammogram Images	Hard	46.02	46.44	45.30	45.91	45.98
	Soft	43.49	43.80	43.68	43.26	43.13

Effectiveness of the proposed classification algorithm for mammogram images have been thoroughly tested using a MIAS dataset. MIAS dataset has been divided into parts: 70% for training and 30% testing and obtained features have been normalized to form a fuzzy value between $[0,1]$. For different experimental setups, at least 10 times, train and test data were selected randomly. From Table-3, it can observe that soft threshold provides better classification rate than hard threshold. In general, de-nosing filters perform well for different scenarios. The highest classification rate occurs with filter db3 (Level 4) with accuracy 62.12 % (soft threshold) with cpu time 0.0026sec. Table 3 showing data partitioning 60:40 with 10 data fold whereas Table 4 shows data partitioning 70:30 with 10 data fold.

Table-3. Classification accuracy and CPU time with 60:40.

Wavelet de-noising filters with different decomposition levels		Fuzzy soft set classifier	
		Accuracy (%)	**CPU time (Sec)**
Daubechies db3 (Level 1)	Hard thresholding	55.23	0.0031
	Soft thresholding	54.77	0.0031
Daubechies db3 (Level 4)	Hard thresholding	51.82	0.0035
	Soft thresholding	57.27	0.0036
Sym8 (Level 1)	Hard thresholding	53.64	0.0031
	Soft thresholding	53.86	0.0036
Sym8 (Level 4)	Hard thresholding	59.77	0.0031
	Soft thresholding	57.27	0.0033

ARPN Journal of Engineering and Applied Sciences

Table-4. Classification accuracy and CPU time with 70:30.

Wavelet de-noising filters with different decomposition levels		Fuzzy soft set classifier	
		Accuracy (%)	**CPU time (Sec)**
Daubechies db3 (Level 1)	Hard thresholding	53.33	0.0032
	Soft thresholding	57.58	0.0035
Daubechies db3 (Level 4)	Hard thresholding	54.55	0.0026
	Soft thresholding	62.12	0.0026
Sym8 (Level 1)	Hard thresholding	56.36	0.0027
	Soft thresholding	54.85	0.0028
Sym8 (Level 4)	Hard thresholding	59.09	0.0038
	Soft thresholding	57.58	0.0028

Table-3 and Table-4 illustrate the comparison of two data partition where it can be observed that data partition 70:30 provide better accuracy then data partition 60:40.

Presence /absence of noise are contributing factors towards affecting classification accuracy. Therefore, noise can be added in mammogram images during data acquisition, preprocessing or any other stage of image processing and how to reduce noise becomes an important issue. Therefore, Table-5 shows the comparison of classification accuracy in the presence/absence of noise in mammogram images.

It is observed that presence of noise badly affect the classification accuracy. The proposed method with de-noising filter provides accuracy 62.12% (with noise) and 63.64% (without noise) which is comparatively better than other reported techniques such as NN and Bayesian. However, the classifiers SVM and K-NN have better accuracy without noise. Moreover, the six statistical features which are mean, variance, skewness, kurtosis, contrast and smoothness are strong feature set. These feature set help in producing better classification results with and without noise.

Table-5. Classification accuracy with and without noise.

Technique	Mammogram with noise accuracy (%)	Mammogram with accuracy (%) without noise
NN+ features [4]	58.2 (Poisson noise)	63.6
	56.3 (Salt and Pepper noise)	
Bayesian+ features [4]	59.1 (Poisson noise)	63.1
	57.5 (Salt and Pepper noise)	
Proposed method	62.12(Gaussian noise)	63.64

CONCLUSIONS

This study applied a classification algorithm based on fuzzy soft set with different wavelet de-noising filters. From the observations, it can be concluded that db3 is more appropriate filter while compared with the other wavelet filters. This paper provides an alternative de-noising method for mammogram images. Moreover, from the theoretical point of view, this study contributes to the body of knowledge by investigating determinant factors that influenced the classification algorithm.

Thus, this study contributes by extending the robustness of fuzzy soft theory into examining mammogram images within medical image classification domain. To the best of our knowledge, this theory is mainly used within texture classification, gene expression and decision making problems context. In the future work, the researcher should incorporate similarity measure based on matching function for mammogram images classification.

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