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Texture Feature Extraction for Mammogram Images Using Biorthogonal Wavelet Filter via Lifting Scheme

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Abstract: ***Feature extraction is an important part in Content-based image retrieval (CBIR).It is an active research area over the past few decades. In this paper texture feature extraction of mammogram images are done. Biorthogonal wavelet filter via lifting scheme is used for the extraction of texture features. Maximum likelihood estimator (MLE) is used for texture feature estimation. Here Digital Database for Screening Mammography (DDSM) is used as the database. Here biorthogonal wavelets are used in the lifting scheme to get texture feature vectors of mammogram images. By using lifting scheme in all biorthogonal wavelets, predict and update filter coefficients are also got. These coefficients will be adapted later and thus we can find the optimal wavelet filter bank for increasing the retrieval performance of the retrieval system. By using lifting scheme methodology decomposition of images are done and thus got approximation and detail coefficients of image.***

Keywords: Texture feature extraction, biorthogonal wavelets, lifting scheme, DDSM database, mammogram

1. Introduction

In the last decade a great number of digital medical images have been produced in hospitals[1]-[5].Large-scale image databases pull together various images, including X-ray, computed tomography , magnetic resonance imaging , ultrasound , nuclear medical imaging, endoscopy, microscopy, and scanning laser ophtalmoscopy[1] [2] [3][8] . The most significant part of image database management is how to successfully retrieve the desired images by means of a description of image content. This method of searching images is known as content-based image retrieval (CBIR) [1] -[9]. Content-based image retrieval has been a dynamic research area for more than a decade [1]. The principal objective is to retrieve digital images based not on textual observations but on features derived directly from image data [6]. These features are then stored together with the image and serve as an index. Retrieval is frequently done in a query by example fashion where a query image is provided by the user. The retrieval system is then searching through all images so as to find those with the most similar indices which are returned as the candidates most related to the query [5] ,[6]. A large variety of features have been proposed in the CBIR literature. In general, they can be grouped into several categories: colour features, texture features, shape features, sketch features, and spatial features [1] [6] [7].

The main contribution of the work is to present a CBIR methodology for mammograms. The main aim is to find out the optimal wavelet approach for texture feature extraction in mammogram retrieval using DDSM database. The general architecture of CBIR systems is shown in figure 1. Here using an adaptive separable wavelet transform for content based mammogram retrieval [1] [2]. Adaptive separable wavelet approach is used in a previous work by Lamard et al. [1] [2]. There they used adaptive separable wavelet approach for feature extraction in different medical images and got 70.91% of retrieval accuracy for mammogram images in DDSM database when five images are returned by the system .The main aim is to get the precision rate greater than 70.91% for DDSM databases.

The DDSM project is a collaborative effort concerning the Massachusetts General Hospital, the University of South Florida and Sandia National Laboratories [1]. The primary function of the database is to facilitate research in the improvement of aid computer algorithms screening. The database contains about 2,500 studies [1]. Each study includes two images of each breast, together with some related patient information (age at time of study, ACR breast density rating) and image information (scanner, spatial resolution). The expert diagnosis ('normal', 'benign' or 'cancer') is also available [1].

Feature extraction technique is a very significant step in content based image retrieval [2] [6] [7]. Here it is extracting the texture feature of the mammogram. For this it is using wavelet approach for texture feature extraction. Adaptive separable wavelet approach is used in a previous work by Lamard et al [1] [2]. There they used adaptive separable wavelet approach for feature extraction in different medical images and got 70.91% of retrieval accuracy for mammogram images in DDSM database when five images are returned by the system. Here the aim is to get the precision rate greater than 70.91% for DDSM databases. So it is going to use a separable adaptive wavelet transform to improve the result. Quellec and Lamard used a pyramidal decomposition scheme and they used the 3rd decomposition level for designing the filter. By using different decomposition schemes and level it is able to improve the retrieval accuracy of the filter bank. Quellec and Lamard also used genetic algorithm for optimization process. So here it is trying different optimization procedures in the filter bank to find out the best optimization procedure for improving the retrieval accuracy. The related literatures for this project work is collected and studied. It is found that the literatures for retrieval of mammograms from DDSM database are limited. Application of simulated annealing, a different approach for adapting the wavelet is suggested as a modification from the base paper. From the literatures it is understood that simulated annealing is better than genetic algorithm. Hence, there is a high chance for better retrieval performance.

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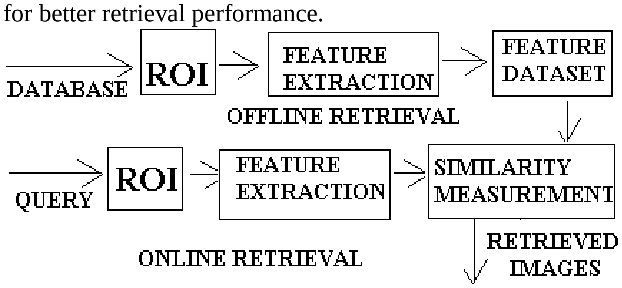

Figure 1: The general architecture of CBIR

The set up of this article is as follows. Texture extraction using biorthogonal filter bank via lifting scheme is discussed in section 2. Then discussing about the results obtained in section 3. And section 4 gives the conclusion of the paper.

2. Biortogonal Wavelet Filter Bank via Lifting Scheme

In this paper, the objective is to get the texture feature vectors of mammogram images. Biorthogonal wavelet filter via lifting scheme is the methodology used here for texture feature extraction [1][2]. Thus decomposition of images is occurred and got approximation and detail coefficients of images. Predict and update filter coefficients is obtained by applying all biorthogonal wavelets in lifting schemes.

2.1 Biorthogonal Wavelets

A biorthogonal wavelet is a wavelet where the associated wavelet transform is invertible but not necessarily orthogonal. Designing biorthogonal wavelets allows more degrees of freedom than orthogonal wavelets. One additional degree of freedom is the possibility to construct symmetric wavelet functions [1].

In the biorthogonal case, there are two scaling functions, Φ and Φbar which may generate different multiresolution analyses, and accordingly two different wavelet functions ϕ and ϕbar.

There are different types of biorthogonal wavelets are there. They are bior 1.1, bior 1.3, bior 1.5, bior 2.2, bior 2.4, bior 2.6, bior 2.8, bior 3.1, bior 3.5, bior 3.7, bior 3.9, bior 4.4, bior 5.5, bior 6.8.All these biortogonal wavelets are used in mammogram images to get the predict and update coefficients by lifting scheme. All these biortogonal wavelets have different scaling and wavelet functions.

2.2 Lifting scheme

The lifting scheme is a technique for both designing wavelets and performing the discrete wavelet transform [1]. Actually it is useful to merge these steps and design the wavelet filters while performing the wavelet transform. This is then called the 2nd generation wavelet transform. . The technique was introduced by Wim Sweldens. The discrete wavelet transform applies several filters separately to the same signal. In contrast to that, for the lifting scheme the signal is divided like a zipper. Then a series of convolution-accumulate operations across the divided signals is used.

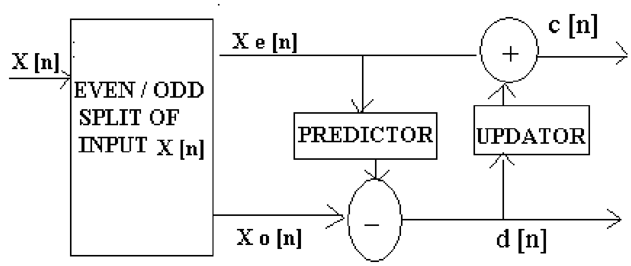

Figure 2: Lifting Scheme

The lifting scheme is particularly suited to design a adapted wavelet basis, we can generate several biorthogonal filters, using an optimization procedure, in order to find the wavelet basis maximizing the retrieval performance of the CBIR system.

There are three main steps in the wavelet decomposition via lifting scheme. The lifting scheme wavelet decomposition is shown in Figure 2.There are three main steps in the wavelet decomposition via lifting scheme [1] [2].

1. Split: the input signal x[n]is split into its odd x_o[n] and even x_e[n]coefficients.
2. Predict: This step produces the wavelet coefficients d[n] as the error in predicting x_o[n] from x_e[n] using predict filter.
P: d[n] = x_o[n] –P (x_e[n]).
3. Update: Combine x_e[n]and d[n] to obtain scaling coefficients representing an approximation to the original input signal x[n]. This is done by using the update filter.
U: c[n] = x_e[n] +U (d[n])

LetN_p and N_u be the length of the linear filters P and U. To form a biorthogonal wavelet, filters P and U only have to satisfy the below conditions:

$$\sum_{i=1}^{N_P} P_i = 1 \quad (1)$$

$$\sum_{i=1}^{N_u} U_i = \frac{1}{2} \quad (2)$$

There are then$N_P + N_U - 2$ undetermined coefficients. Wavelets designed by the lifting scheme have a support length equal to s/t, where s is the support of the low-pass filter and t is the support of the high-pass filter:

$$s = 2\,(N_p+N_u)-3 \quad (3)$$

$$t=2N_p-1 \quad (4)$$

Thus by using the lifting scheme in all biorthogonal wavelets, predict and update filter coefficients are obtained. These coefficients are required for the adaptation of both predict and update filters. To adapt the wavelet filter, within the lifting scheme framework, is to browse the space of biorthogonal filter banks, by an optimization procedure, and to select the filter bank that maximizes the adaptation criterion. The first Np - 1 (resp. Nu _ 1) coefficients of P (resp. U) can be freely chosen, and the last coefficient of both vectors are computed in order to satisfy equations. (1 & 2); as a result, it will have Np + Nu - 2 degrees of freedom.

2.3 Maximum likelihood estimation (MLE)

It is a statistical method used for fitting statistical model to data, and it also gives estimates for the model's parameters [2]. In this paper MLE function is used to generate the feature vectors using the biorthogonal wavelet coefficient MLE (of generalized Gaussian distribution in each subband of wavelet decomposition to form the features [2]. To characterize textures, modeling the distribution of transformed coefficients in each sub band with zero-mean generalized Gaussian functions has done [2]. A generalized Gaussian function may be expressed as

$$p(x;\alpha,\beta) = \frac{\beta}{2\alpha\gamma\left(\frac{1}{\beta}\right)} e^{-\left(\frac{|x|}{\alpha}\right)^{\beta}} \quad (5)$$

$$\gamma(z) = \int_0^{\infty} e^{-t} t^{z-1}\,dt,\ z > 0 \quad (6)$$

The CDF of a zero-mean generalized Gaussian is given below

$$cdf(x;\alpha,\beta) = \frac{1}{2} + \mathrm{sign}(x)\frac{\gamma\left(\frac{1}{\beta},\left(\frac{|x|}{\alpha}\right)^{\beta}\right)}{2\gamma\left(\frac{1}{\beta}\right)} \quad (7)$$

$$\gamma(s,z) = \int_0^{z} e^{-t} t^{s-1}\,dt,\ z > 0 \quad (8)$$

Finally the maximum likelihood estimator (α,β) of CDF is estimated by the method proposed by Do et.al [7] is used here.

3. Results and Discussion

Texture features of different mammogram images are extracted using lifting scheme and biorthogonal wavelets. Table 1 shows the different texture feature vectors obtained from 4 different classes of mammogram images by using bior 1.1 wavelet. Approximation and detail feature vectors of all those images are obtained. Thus comparison of feature vectors of different images can be shown. Table 2 shows the predictor and updater filter coefficients for all different types of biorthogonal wavelets. These coefficients will be later needed for the adaptation of biorthogonal wavelet filter. Figure 5 shows approximation and detail coefficients (CA,CD,CH,CV) of 4 different classes of mammogram images after decomposition 1)micro calcification image 2)circumscribed image 3)normal image 4)spiculated image. By using lifting scheme methodology decomposition of images are done in different levels and thus got approximation and detail coefficients of images and getting better results in 4^{th} level. This is shown in figure 6.In the figure a micro calcification image is taken and decomposition is done in 3 different levels and best result is obtained in 4^{th} level. So it's concluded that 4^{th} level decomposition is better for mammogram retrieval by this approach.

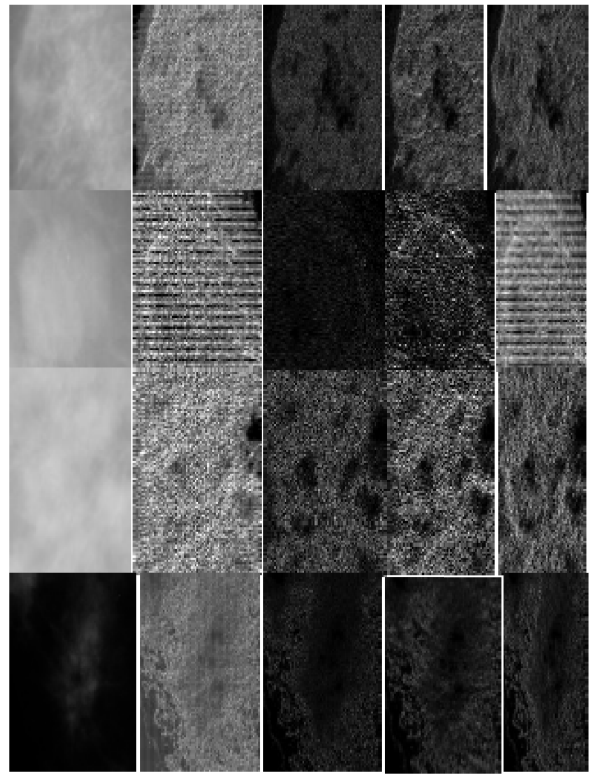

Figure 3: CA, CD, CH, CV of 4 classes of mammogram images after decomposition 1) micro calcification image 2) circumscribed image 3) normal image 4) spiculated image

Table 1: Texture features extracted from 4 different Classes of mammogram Images by Using Bior 1.1 wavelet

Images	*Extracted features using bior 1.1 wavelet-level 3*			
	fA	*fH*	*fV*	*fD*
Micro-calcification	[2.025, 7.846]	[-0.407 , 435.08]	[-8.56 ,403.6]	[-0.2979 , 269.297]
Circumscribed	[2.1093, 8.0893]	[18.4997 , 300.277]	[-16.239, 256.035]	[-0.0544, 103.143]
Normal	[2.4479 ,9.3726]	[0.9011, 16.2419]	[0.79931, 371.3]	[0.2424, 234.7]
Spiculated	[1.2608, 7.2612]	[-4.1502, 198.003]	[-0.5253, 200.401]	[0.1337, 106.4108]

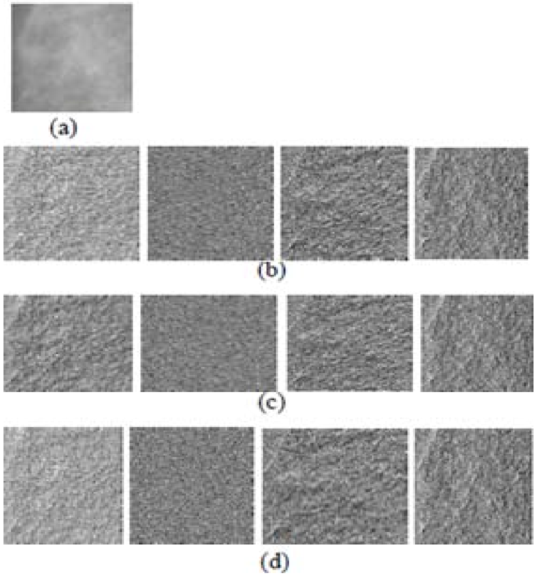

Figure 4: CA, CD, CH, CV of a mammogram image after different levels of decomposition.(a) input image (b) level 2 (c) level 3 (d) level 4

Table 2: Predictor and updater filter coefficients

Wavelet	*Updater Filter Coefficients*	*Predictor Filter Coefficients*
Bior 1.1	[-1]	[0.500]
Bior 1.3	[-1]	[-0.0625, 0.500 , 0.0625]
Bior 1.5	[-1]	[0.0117, -0.0859 ,0.5000 0.0859, -0.0117]
Bior 2.2	[-0.50, -0.500]	[0.2500 , 0.2500]
Bior 2.4	[-0.50, -0.500]	[-0.0469 , 0.2969, 0.2969, -0.0469]
Bior 2.6	[-0.500 , -0.5000]	[0.0098 , -0.0762, 0.3164, -0.0762, 0.0098]
Bior 2.8	[-0.500, -0.5000]	[-0.0021 , 0.0204 , -0.0954, 0.3271, 0.3271 ,0.0954, 0.024 , -0.0021]
Bior 3.1	[-0.375, -1.1250]	[-0.3333] [0.4444]
Bior 3.3	[-0.375, -1.1250]	[-0.3333] [0.0833, 0.4444 ,0.0833]
Bior 3.5	[-0.375 ,-1.1250]	[-0.3333] [0.0174, -0.1181 , 0.4444, 0.1181, -0.0174]
Bior 3.7	[-0.375, -1.1250] [-0.0038, 0.0326 -0.1370, -0.4444 0.1370, -0.0326 , 0.0038]	[-0.3333]
Bior 3.9	[-0.375 -1.1250] [8.5449, -0.0089 , 0.0445 , -0.1490,-0.4444 0.1490 , -0.4445 0.0089 ,-8.5449]	[-0.3333]
Bior 4.4	[-1.5861] [-0.082, -0.082]	[1.0796 , -0.0530] [0.4435 , 1.5761]
Bior 5.5	[4.9933] [5.5858, 5.5858] [0.2901, 0.2901]	[-0.1834 , -0.0044] [-3.0949 , 0.1732] [-3.4472]
Bior 6.8	[0.2735 , 0.2735] [-0.286 , -0.2865] [0.0998 , -0.3438 -0.3438 ,0.0998]	[-2.6590] [3.8778 , -3.2687] [-0.5486 , 2.9418]

4. Conclusion

Here texture feature extraction of mammogram images is done. Biorthogonal wavelet filter via lifting scheme is used for the extraction of texture features. And these texture feature vectors will be used for retrieval purposes. Here texture feature extraction of mammograms from Digital Database for Screening Mammography (DDSM) is presented. In this paper biorthogonal wavelets are used in the lifting scheme to get texture feature vectors of mammogram images. By using lifting scheme in all different biorthogonal wavelets, predict and update filter coefficients are also obtained. These coefficients will be needed later for the adaptation and thus we can find the optimal wavelet filter bank for increasing the retrieval performance of the retrieval system. By using lifting scheme methodology decomposition of images are done in different levels and thus got approximation and detail coefficients of images and getting best results in 4^{th} level. So it's concluded that 4^{th} level decomposition is better in the approach. The future scope of this paper is to try with different optimization techniques like simulated annealing to improve the retrieval performane of the CBIR system.

References

[1] G. Quellec, M. Lamard, G. Cazuguela, B. Cochener, C. Roux ,"Wavelet optimization for content-based image retrieval in medical databases", Medical Image Analysis14(2010),pp.227–241
[2] G. Quellec, M. Lamard, G. Cazuguel, B. Cochener, C. Roux, "Adaptive non-separable wavelet transform via lifting and its application to content-based image retrieval", IEEE transactions on image processing, pp. 1-10
[3] G .Quellec, M. Lamard, G. Cazuguel, B. Cochener ,C.Roux,"Multimodal medical case retrieval using the dezert-smarandache theory", 30th Annual International IEEE EMBS ConferenceVancouver, British Columbia, Canada, August20-24,2008,pp.394-397
[4] C.-H.Wei, C.-T. Li, Y. Li, "Content-based retrieval for mammograms", Artificial Intelligence for Maximizing Content Based Image Retrieval, 2008, *pp.313-339*
[5] Weiwei Wang, LihuaLi,Wei Liu, Weidong Xu, " A New Two-Stage Hierarchical Framework for Mammogram Retrieval", Science Foundation of Zhejiang Province, pp.1-4
[6] Do, M.N., Vetterli, M., 2002. "Wavelet-based texture retrieval using generalized Gaussian density and Kullback–Leibler distance", IEEE Transactions on Image Processing 11 (2), pp.146–158
[7] Manimala Singha and K.Hemachandran, " Content Based Image Retrieval using Color and Texture", Signal& Image Processing: An International Journal (SIPIJ) Vol.3, No.1,February2012,pp.39-56
[8] Ray-I Chang , Shu-Yu Lin , Jan-Ming Ho , Chi-Wen Fann , and Yu-Chun Wang, " A Novel Content Based Image Retrieval System using K-means/KNN with Feature Extraction", ComSIS Vol. 9, No. 4, Special Issue, December 2012,pp. 1645-1661

[9] Latika Pinjarkar,Manisha Sharma, Kamal Mehta, “Comparison and Analysis of Content Based Image Retrieval SystemsBased On Relevance Feedback”, Journal of Emerging Trends in Computing and Information Sciences,Vol. 3, No. 6, July 2012,pp.833-837

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