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Content Based Medical Image Retrieval Using Lifting Scheme Based Discrete Wavelet Transform

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***Abstract*—Content based image retrieval technology has been proposed to benefit not only management of increasingly large image collection, but also to aid clinical care, biomedical research and education. In this paper, lifting scheme is proposed for content based retrieval method for diagnosis aid in medical field. Content-based image retrieval (CBIR) techniques could be valuable to radiologists in assessing medical images by identifying similar images in large archives that could assist with decision support. DWT is any wavelet transform for which the wavelets are discretely sampled. Although classical wavelet transform is effective in representing image feature and thus is suitable in CBIR, it still encounters problems especially in implementation, e.g. floating-point operation and decomposition speed, which may nicely be solved by lifting scheme. Lifting scheme is simplest and efficient algorithm to calculate wavelet transform. Lifting scheme used as feature in CBIR which has intriguing properties as faster implementation, low computation, easier to understand and can also be used for irregular sampling. Lifting scheme allows us to implement reversible integer wavelet transform. After extracting features using lifting scheme for both query image and database images for breast cancer images, Manhattan distance is used to calculate the similarity between the images for proper diagnosis which permits radiologist to identify whether the query image is malignant or normal tissue.**

***Keywords*—Content based image retrieval(CBIR),Discrete wavelets transform, lifting scheme, medical retrieval, image database.**

I. INTRODUCTION

In CBIR system, the term (CBIR)[1]describes the process of retrieving desired images from a large collection on the basis of features (such as colour, texture and shape) that can be automatically extracted from the images themselves. The features which are extracted from an image can uniquely identify an image from others. The extraction of features from the image pixels is termed as feature extraction. Using the extracted features from the process of feature extraction, similarity betweenindexed image and query image is measured. Texture is the main feature utilized in image processing and computer vision to characterize the surface and the structure of given object or a region. The method to characterize texture fall into two categories: structure and statistical. Structural method includes gabor transform and 2-D wavelet transform, statistical methods are first order,second order statistics, run length matrix and auto correlation function. Lifting scheme [3]-[6] is one of the structural method. The main feature of lifting scheme is that all constructions are derived in the spatial domain. It is the simplest and efficient algorithm to calculate wavelet transform and is used to generate second generation wavelets, which are not necessarily translation and dilation of one particular function.

Constructing wavelets using lifting scheme consists of three steps: The first step is split phase that split data into odd and even sets. The second step is predict step, in which odd set is predicted from even set. Predict phase ensures polynomial cancellation in high pass. The third step is update phase that will update even set using wavelet coefficient to calculate scaling function.Update stage ensures preservation of moments in low pass as shown in fig 3.

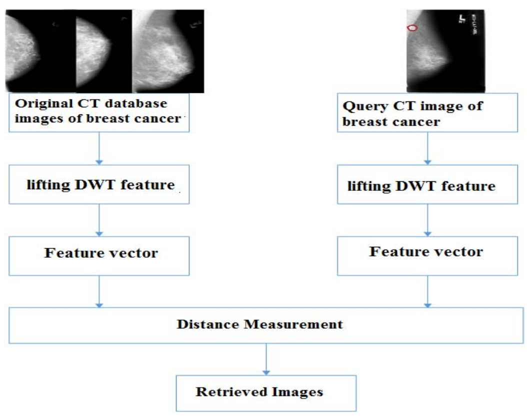

Fig 1. Block diagram of proposed method for CBIR

A. Reasons for the choice of lifting scheme

Lifting scheme of wavelet transform for the CBIR is used because lifting scheme is having following advantages over conventional wavelet transform technique.

- It allows a faster implementation of the wavelet transform. It requires half number of computations as compare to traditional convolution based discrete wavelet transform. This is very attractive for real time low power applications.

- The lifting scheme allows a fully in-place calculation of the wavelet transform. In other words, no auxiliary memory is needed and the original signal can be replaced with its wavelet transform.
- Lifting scheme allows us to implement reversible integer wavelet transforms. In conventional scheme it involves floating point operations, which introduces rounding errors due to floating point arithmetic. While in case of lifting scheme perfect reconstruction is possible for loss-less compression. It is easier to store and process integer numbers compared to floating point numbers.
- Easier to understand and implement.
- It can be used for irregular sampling.

II. WAVELET APPROACHES

The basic idea of wavelet transform is to exploit correlation, structure present in most real life signals to build sparse approximations. The correlation structure is local in both frequency and time domain. Traditional wavelet transform use wavelet filters to build time frequency localization.

A. Classical Discrete Wavelet Transform

Discrete wavelet transform (DWT) separates an image into a lower resolution approximation image(LL) as well as horizontal (HL), vertical(LH), and diagonal(HH) detail components. The process can then be repeated to compute multiple “scale “wavelet decompositions, as in the two scale wavelet transform shown in the figure 2.

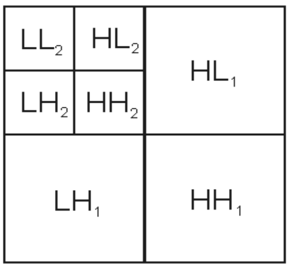

Fig 2. 2 Scale 2-Dimensional Discrete Wavelet Transform

The classical implementation is realized by the convolution of the input signals with lowpassfilter(af1) and highpass filter (af2). [2]

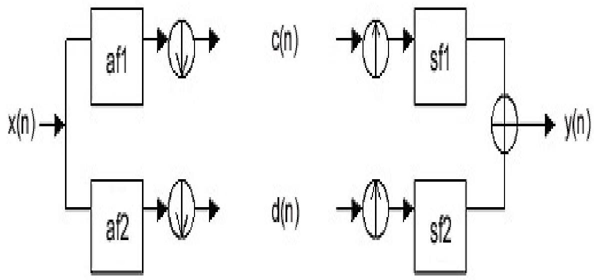

Fig 3. 2-Channel Perfect Reconstruction Filter Bank

The analysis filter bank decomposes the input signal x(n) into two subband signals, c(n) and d(n). The signal c(n) represents the low frequency (or coarse) part of x(n), while the signal d(n) represents the high frequency (or detail) part of x(n). The analysis filter bank first filters x(n) using a lowpass and a highpass filter. We denote the lowpass filter by af1 (analysis filter 1) and the highpass filter by af2 (analysis filter 2). As shown in the figure, the

output of each filter is then down-sampled by 2 to obtain the two subband signals, c(n) and d(n).

B. Lifting Scheme Based Discrete Wavelet Transform

Discrete wavelet transform performs multi stage decomposition. In this paper, fast and efficient way of finding DWT using lifting scheme is used. It de-correlates the signal at different resolution levels. Basic polynomial interpolation is used to find high frequency values. It is also used to construct scaling functions in order to find out low frequency values.

Consider the sequence of samples $\lambda_{0,k}$ (Where, k=0 to n-1) at some approximation level say “level 0”. This sequence can be transformed into two other sets at “level -1*”. First of all, this sequence is divided into set of odd and even samples. Such splitting is sometimes known as lazy wavelet transform. Doing this it will not help us to represent signal compactly. This sequence is transformed into coarser signal $\lambda_{-1,k}$(Where value of k= 0 to n/2-1) and detail signal $\Upsilon_{-1,k}$ (Where k=0 to n/2-1) by predict and update stage of lifting scheme of wavelet transform.as shown in fig 4. Lifting scheme consists of three steps:

- Split (Lazy wavelet transform)
- Predict (Dual lifting)
- Update (Primal lifting)

Split (Lazy wavelet transform): This stage splits entire set of signal into two frames. One frame consists of even index samples such as $\lambda_{0,0}$, $\lambda_{0,2}$ ……. $\lambda_{0,2k}$. We will call this frame as $\lambda_{-1,k}$. Other frame consists of odd samples such as $\lambda_{0,1}$, $\lambda_{0,3}$, ……. $\lambda_{0,2k+1}$. We will call this frame as $\Upsilon_{-1,k}$. Each group consists of one half samples of the original signal. Splitting the signal into two parts is called lazy wavelets, because we have not performed any mathematical operations.

If we remove any of the frames, then signal information will be lost.

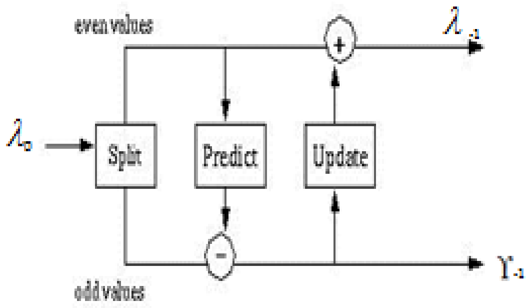

Fig 4. lifting steps for forward wavelet transform

New sequence can be given as: $\lambda^*_{-1,k} = \lambda_{0,2k}$ where k∈ Z.

The sequence $\Upsilon_{-1,k}$ can be given as: $\Upsilon_{-1,k} = \lambda_{0,2k+1}$, Where k ∈ Z.

$\Upsilon_{-1,k}$ sequence gives us idea about how much information was lost or in other words we can say that it gives information about how we can recover original sequence $\lambda_{0,k}$ from transformed sequence $\lambda_{-1,k}$. The difference between $\lambda_{0,k}$ and $\lambda_{-1,k}$ can be encoded as wavelet coefficient.

Splitting of data sequences can be done with different methods. We can cut data sequence into left part and right part directly, but in that case, values are hardly correlated. Predicting right half of signal from left half and vice-versa is a tough job. Hence, better method is to interlace the two sets by odd and even frames.

Predict (Dual lifting): The even and odd samples are interleaved. If the signal is having locally correlated structure, then even and odd samples are highly correlated. In that case, it is very easy to predict odd samples from even samples. For example, in case of triangular and saw-tooth waves, odd sample is average of two neighboring even samples, hence majority of the wavelet coefficients are zero. In order to achieve maximum data compression, prediction must be powerful. In order to build powerful predictor, we must know nature of the signal. The prediction does not necessarily have to be linear. Cubic or other higher order predictor can be used. Interpolating subdivision is used to find out predictor.

We would like to represent data more compactly in order to reduce storage requirement as well as to reduce transmission rate. If we can use powerful prediction mechanism, we can represent data more compactly. Consider that $\Upsilon_{-1,k}$ does not contain any information (Odd values perfectly predicted from even values) then we can simply replace $\lambda_{0,k}$ by smaller set $\lambda_{-1,k}$. This situation is practically impossible for real time data. So we have to find out some correlation present in the data and build prediction mechanism based on correlation structure. If we can find out prediction operator P independent of data so that

$$\Upsilon_{-1,k} = P(\lambda_{-1,k}) \qquad (1)$$

In practice, it might not be possible to exactly predict $\Upsilon_{-1,k}$ from $\lambda_{-1,k}$. However, $P(\lambda_{-1,k})$ is likely to be closed to $\Upsilon_{-1,k}$. Thus, we want to replace $\Upsilon_{-1,k}$ with difference between itself and its predicted value. If prediction is reasonable then difference will contain much less information. We can denote this with Equation

$$\Upsilon_{-1,k} = \lambda_{0,2k+1} - P(\lambda_{-1,k}) \qquad (2)$$

If signal is correlated, the majority of wavelet coefficients are small. For example, in case of linear signals such as saw-tooth and triangular waveform odd sample is average of two even samples, where prediction function can be given as:

$$P(\lambda_{-1,k}) = ½(\lambda_{-1,k} + \lambda_{-1,k+1}) \qquad (3)$$

$$\Upsilon_{-1,k} = \lambda_{0,2k+1} - ½(\lambda_{-1,k} + \lambda_{-1,k+1}) \qquad (4)$$

Predicted value

In terms of frequency content, wavelet coefficients capture high frequency present in the signal. We are happy, if these wavelet coefficients are small or zero. This represents enough information to move from $\lambda_{-1,k}$ to $\lambda_{0,k}$. The sequence $\lambda_{-1,k}$ is further divided into two set $\lambda_{-2,k}$ and $\Upsilon_{-2,k}$. Where, $\Upsilon_{-2,k}$ is the difference between $\lambda_{-1,2k+1}$ and predicted values from $\lambda_{-1,2k}$. To get more compact representation, we can iterate this scheme to higher levels such as $\lambda_{-3,k}$, $\lambda_{-4,k}$ ….and so on. After "n" steps, original data will be replaced by { $\lambda_{-n,k}$, $\Upsilon_{-n,k}$, $\Upsilon_{-n+1,k}$, $\Upsilon_{-n+2,k}$ …….$\Upsilon_{-1,k}$ }

Update (Primal lifting): The coarser signal must have same average value that of original signal. To do this, we require lifting the $\lambda_{-1,k}$ with help of wavelet coefficients $\Upsilon_{-1,k}$. After lifting process, mean value of original signal and transformed signal remains same. We require constructing update operator U for this lifting process.

$$\lambda_{-1,k} = \lambda_{-1,k} + U(\Upsilon_{-1,k}) \qquad (5)$$

In order to maintain same properties among all the λ coefficients throughout all the levels, we require to find out some scaling function. One way to achieve this scaling function is to set all $\{\lambda_{0,k}$, k = 0 to n$\}$ to zero except $\lambda_{0,0}$ which is set to 1. Then run interpolating subdivision to infinity. The resulting function is scaling function that will help us to create real wavelet, which will heritage properties of original signal.

In update phase, scaling function is calculated from previous value of wavelet coefficients $\Upsilon_{-1,k}$. The equation (5) represents update phase.

$$\lambda_{-1,k} = \lambda_{0,2k} + ¼\,(\lambda_{0,2k-1} + \lambda_{0,2k+1}) \quad (6)$$

$$\lambda_{-1,k} = \lambda_{-1,k} + ¼(\Upsilon_{-1,k-1} + \Upsilon_{-1,k}) \qquad (7)$$

The calculation of update phase is in-place to reduce memory requirements. Even locations are over-written with the averages and the odd ones with the details.

In this case, we have used linear interpolation, so we call it a linear wavelet transform..In order to achieve multilevel decomposition, $\lambda_{-1,k}$ is further decomposed into coarser and detail parts using split, predict and update stage and we get $\lambda_{-2,k}$ and $\Upsilon_{-2,k}$. This process can be repeated N number of time. Where, N=log2(n) and “n” is frame size. Fig.5 represents multilevel decomposition using lifting scheme.

Thus if we start with frame size of 512 samples, at the first level it will be decomposed into 256 coarser coefficients and 256 detail coefficients. Again 256 coarser coefficients are further decomposed into 128 coarser coefficients and 128 detail coarser coefficients and so on ….

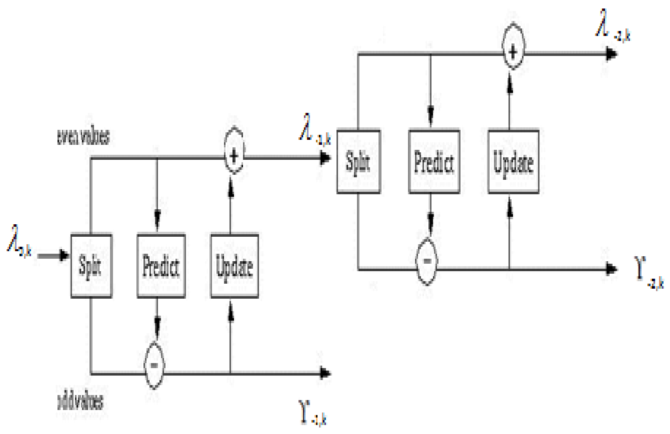

Figure 5. Multi-level wavelet transform with lifting scheme

III. DISTANCE MEASURE

Manhattan distance:

Manhattan distance is given by

$$\sum_{i=1}^{n} |xi - yi|$$

The minimum distance value signifies an exact match with the query. Manhattan distance is not always the best metric. The fact that the distances in each dimension are modulated before summation, places great emphasis on those features for which the dissimilarity is large. Hence it is necessary to normalize the individual feature components before finding the distance between two images.

IV. METHODOLOGY

In order to evaluate the feasibility of lifting DWT features for medical images consider the mias database [7] which consist of breast cancer images of 512 x 512 in size and having 16-bit gray level resolution. The database consists of 1000 images out of which 500 are cancer images and 500 are normal images which are stored in JPEG format. In order to increase retrieval efficiency lifting DWT is used.

Constructing wavelets using lifting scheme consists of three steps: The first step is split phase that split data into odd and even sets. The second step is predict step, in which odd set is predicted from even set. Predict phase ensures polynomial cancellation in high pass. The third step is update phase that will update even set using wavelet coefficient to calculate scaling function. Update stage ensures preservation of moments in low pass. After extracting the features from query image and database image, Mahanttan distance is used fordistance measure between query image and database images are calculated as shown in fig 1. Similar images are retrieved based on distance measure and count displays number of cancer images in database are as shown in fig6.

V. RESULTS

Breast cancer images are retrieved using lifting DWT feature.Some of the results are displayed when cancer is given as query image within the database. Similarly the results are shown when a normal imagesis given as a query image within database. When query image is given out of the database the following results are shown below

TABLE1
RETRIEVED DATA

S.N.O	QUERY IMAGE TYPE	RETRIEVED NO. OF NORMAL IMAGE	RETRIEVED NO.OF CANCER IMAGE
1	Cancer	205	295
2	Cancer	207	293
3	Cancer	211	289
4	Cancer	211	289
5	Cancer	212	288
6	Cancer	214	286
7	Cancer	216	284
8	Cancer	216	284
9	Cancer	226	274
10	Cancer	227	273
11	Normal	293	207
12	Normal	290	210
13	Normal	290	210
14	Normal	291	209
15	Normal	292	208
16	Normal	283	217
17	Normal	277	233
18	Normal	270	230
19	Normal	268	232
20	Normal	294	206

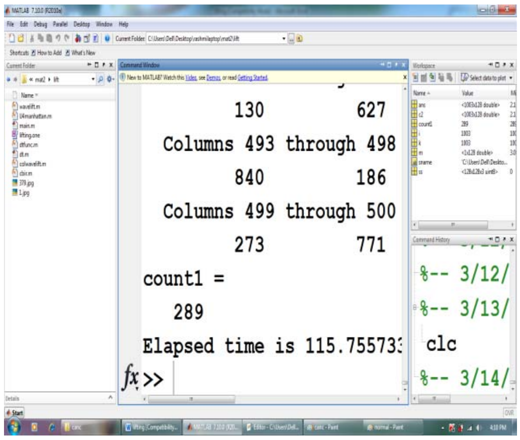

Fig 6. when query is cancer image

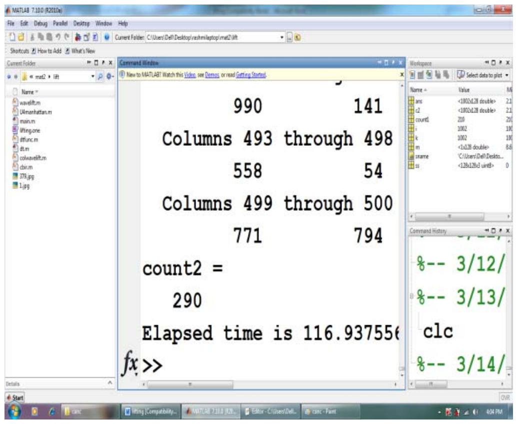

Fig 7. when query image is normal image

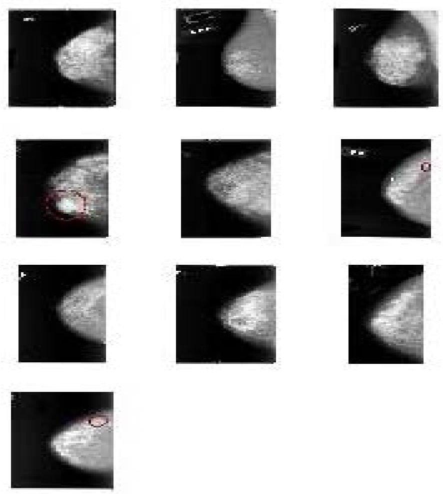

Fig 8. when query image is cancer image within database

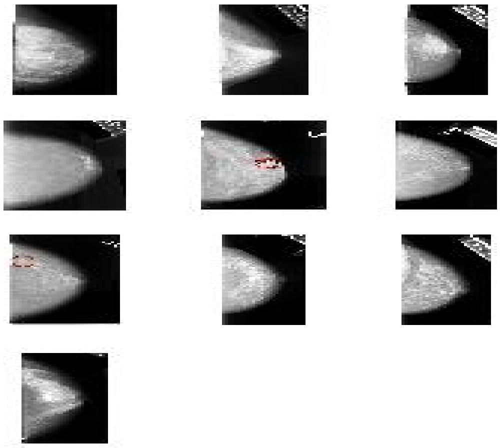

Fig 9. when query image is normal image within database

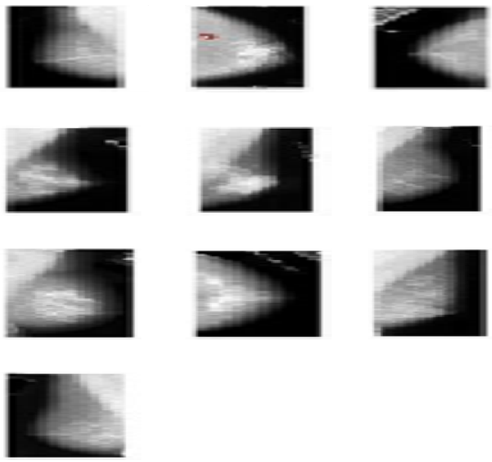

Fig 10. when query image is cancer image and is outside database

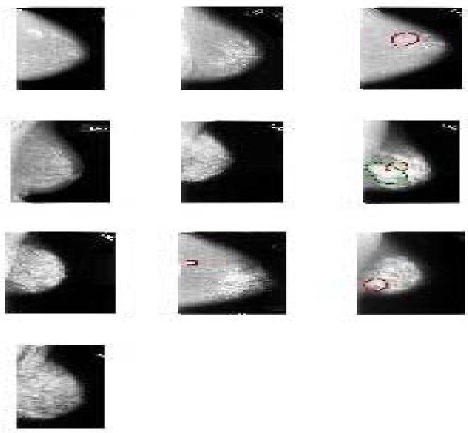

Fig 11. when query image is normal image and is outside database

VI. FURTHER WORK

In this paper,the proposed method lifting DWT for retrieving breast cancer images is helpful for a doctor for a decision support. Texture feature is plays important role in medical fields. So further work by considering different wavelet transform like Amlet, Armlet, Bandlet, Barlet, Bathlet, Beamlet, Binlet etc for improving retrieval efficiency.

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