A New Adaptive Medical Image Coding with Orthogonal Polynomials

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ABSTRACT
In this paper, new adaptive medical image coding technique based orthogonal polynomials transformation is proposed. The input image is first applied with the proposed orthogonal polynomials based modified zero crossing algorithm for edge detection since it is not sensitive to noise and surface irregularities. Then the scan filling algorithm is used to separate the foreground that contains the most important information of medical image from the background region. The orthogonal polynomials based transform coding technique is applied on foreground region for lossless encoding and on background region for lossy encoding. The proposed work uses variable quantization to maintain different quality levels for entire image coding and preserve the most important features that contained in the foreground region of medical image. The experiment results of the proposed technique shows that a higher compression ratio is achieved for coding of medical images with lower computational complexity when compared with existing techniques.

General Terms
Image coding.

Keywords
Edge segmentation, scan filling algorithm, orthogonal polynomials based transform coding.

1. INTRODUCTION
Medical imaging [1,2] plays a significant role in contemporary health care, both as a tool in primary diagnosis and as a guide for surgical and therapeutic procedures. With increasing number of patient data, the compression techniques for digital transmission and storage of medical images have become a necessity [3]. Medical image compression is constrained by the fact that most radiologists are not willing to base a diagnosis on an image that has been compressed in a lossy way. This is partially due to legal reasons (depending on the corresponding country's laws) and partially due to the fear of misdiagnosis because of lost data in the compression procedure [4]. Therefore, only lossless techniques are accepted, which limits the amount of compression to a factor of about 3 (in contrast to factors of 100 or more achievable in lossy schemes). Since the compression rate in lossless model is poor, there is a need for efficient and widely accepted techniques for medical image compression. A possible solution to this dilemma is to offer the image compression techniques which allow an image to be selectively compressed. The parts of the image that contain crucial information (called foreground region) are compressed in a lossless way whereas regions containing unimportant information (called background region) are compressed in a lossy manner. This leads to considerably higher compression ratios as compared to pure lossless schemes while critical information is preserved. The lossless compression scheme reproduces the same original data without any loss of information and the lossy compression scheme produces the approximation of the original data at a higher compression rate. The techniques in the art of compressing the image data can be classified into two categories: i) time-domain (or space domain) encoding and ii) transform domain coding. The time domain techniques that appear practical are mostly of the prediction-compression type. This includes schemes like delta modulation and differential pulse code modulation [5]. The transform coding schemes are proved to be an effective image compression scheme and is the basis of all world standards for lossy compression [6]. These transforms being unitary, conserve the signal energy in the transform domain, but typically most of this energy is concentrated in relatively few samples which are usually the lower frequency samples. The simple and powerful class of transform coding is linear block transform coding, where the entire image is partitioned into a number of non-overlapping blocks and then the transformation is applied to yield transform coefficients. This is necessitated because of the fact that the original pixel values of the input image are highly correlated. Compression is achieved by considering the high energy samples to be sufficient for reconstruction subsequent to transmission, storage or processing. The international compression standards JPEG [7] and JPEG2000 [8] use the Discrete Cosine Transformation [9,10] and wavelet transform [11,12] respectively for image coding.

Many medical image coding systems have been developed both in spatial domain [13-17] and in transform domain [18-22]. The transform based coding techniques provides efficient reduction of the high redundancy and achieves higher compression ratio than the spatial domain techniques. In [18], the selective image compression technique that encodes the Region of Interest (ROI) in lossless mode and remaining region using loss compression such as wavelet and DCT based coders. The wavelet based medical image coding algorithms which modifies the original SPIHT and EBCOT techniques to provide ROI coding feature for chromosome images is reported by Zhongmin liu et . al.[19]. The application of 3-D Hartley transform for encoding the medical images is described in [20]. The 3-D medical image compression using 3-D wavelet coders is presented in [21], wherein the four symmetric and decoupled wavelet transforms are used in first stage and 3-D SPIHT, 3-D SPECK, 3-D BISK are used in second stage of medical image compression. The ECG signal compression algorithm presented in [22], uses modified Embedded Zerotree Wavelet (EZW) coding algorithm and reported better results when comparing with traditional EZW algorithm.

Hence a medical image coding technique that provides higher compression ratio while retaining important information is necessitated, a new low complexity orthogonal polynomials based lossy to lossless medical image coding technique is proposed in this paper. The crucial information present in the medical images is separated as foreground region from the background region with the proposed edge based segmentation algorithm and scan filling algorithm. Since the thresholding type edge detection methods is sensitive to noise and surface irregularities, the edge detection through the identification of zero crossing based on orthogonal polynomials is proposed in this work. After segmentation, the foreground regions are encoded losslessly and background regions are encoded in lossy manner with the proposed orthogonal polynomials based transform coding technique.

This paper is organized as follows: The orthogonal polynomials model for the proposed coding is presented in section 2. The basis operators of the orthogonal polynomials based transformation are given in section 2. The proposed edge detection algorithm and transform coding technique based on orthogonal polynomials are presented in section 4 and 5 respectively. The measurement of performance is given in section 6. The experimental results of the proposed coding and their comparison with existing technique are presented in section 7 and the conclusion is presented in section 8.

2. ORTHOGONAL POLYNOMIALS MODEL

In order to devise a transform coding for lossless image coder, a linear 2-D image formation system is considered around a Cartesian coordinate separable, blurring, point spread operator in which the image I results in the superposition of the point source of impulse weighted by the value of the object function f. Expressing the object function f in terms of derivatives of the image function I relative to its Cartesian coordinates is very useful for analyzing the image. The point spread function M(x, y) can be considered to be real valued function defined for $(x, y) \in X \times Y$, where X and Y are ordered subsets of real values. In case of gray-level image of size $(n \times n)$ where X (rows) consists of a finite set, which for convenience can be labeled as {0, 1, …,n-1}, the function M(x, y) reduces to a sequence of functions.

$$M(i, t) = u_i(t), \quad i, t = 0, 1, \ldots, n-1 \tag{1}$$

The linear two dimensional transformation can be defined by the point spread operator M(x, y) ($M(i, t) = u_i(t)$) as shown in equation (2).

$$\beta'(\zeta,\eta) = \int_{x\in X}\int_{y\in Y} M(\zeta,x)M(\eta,y)I(x,y)\,dx\,dy \tag{2}$$

Considering both X and Y to be a finite set of values {0, 1, 2, …, n –1}, equation (2) can be written in matrix notation as follows

$$|\beta'_{ij}| = (|M|\otimes|M|)^t |I| \tag{3}$$

where $\otimes$ is the outer product, $|\beta'_{ij}|$ are n2 matrices arranged in the dictionary sequence, |I| is the image, $|\beta'_{ij}|$ are the coefficients of transformation and the point spread operator |M| is

$$|M| = \begin{vmatrix} u_0(t_1) & u_1(t_1) & \cdots & u_{n-1}(t_1) \\ u_0(t_2) & u_1(t_2) & \cdots & u_{n-1}(t_2) \\ & \vdots & & \\ u_0(t_n) & u_1(t_n) & \cdots & u_{n-1}(t_n) \end{vmatrix} \tag{4}$$

We consider a set of orthogonal polynomials $u_0(t)$, $u_1(t)$, …, $u_{n-1}(t)$ of degrees 0, 1, 2, …, n-1 respectively to construct the polynomial operators of different sizes from equation (4) for $n \geq 2$ and $t_i = i$. The generating formula for the polynomials is as follows.

$$u_{i+1}(t) = (t-\mu)\,u_i(t) - b_i(n)\,u_{i-1}(t) \text{ for } i \geq 1, \tag{5}$$

$$u_1(t) = t - \mu, \text{ and } u_0(t) = 1,$$

where $b_i(n) = \dfrac{\langle u_i, u_i\rangle}{\langle u_{i-1}, u_{i-1}\rangle} = \dfrac{\sum_{t=1}^{n} u_i^2(t)}{\sum_{t=1}^{n} u_{i-1}^2(t)}$ and

$$\mu = \frac{1}{n}\sum_{t=1}^{n} t$$

Considering the range of values of t to be $t_i = i$, $i = 1, 2, 3, \ldots, n$, we get

$$b_i(n) = \frac{i^2(n^2 - i^2)}{4(4i^2 - 1)}, \qquad \mu = \frac{1}{n}\sum_{t=1}^{n} t = \frac{n+1}{2}$$

We can construct point-spread operators $|M|$ of different size from equation (4) using the above orthogonal polynomials for $n \geq 2$ and $t_i = i$. For the convenience of point-spread operations, the elements of $|M|$ are scaled to make them integers.

3. ORTHOGONAL POLYNOMIALS BASIS

For the sake of computational simplicity, the finite Cartesian coordinate set X, Y is labeled as {1, 2, 3}. The point spread operator in equation (3) that defines the linear orthogonal transformation for image coding can be obtained as $|M| \otimes |M|$, where $|M|$ can be computed and scaled from equation (4) as follows.

$$|M| = \begin{vmatrix} u_0(x_0) & u_1(x_0) & u_2(x_0) \\ u_0(x_1) & u_1(x_1) & u_2(x_1) \\ u_0(x_2) & u_1(x_2) & u_2(x_2) \end{vmatrix} = \begin{vmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{vmatrix} \tag{6}$$

The set of polynomial basis operators O_{ij}^n $(0 \leq i, j \leq n-1)$ can be computed as

$O_{ij}^n = \hat{u}_i \otimes \hat{u}_j^t$

where $\hat{u}_i$ is the $(i + 1)^{st}$ column vector of $|M|$.

The complete set of basis operators of sizes (2×2) and (3×3) are given below.

Polynomial basis operators of size (2×2) are

$$[O_{00}^2] = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix},\ [O_{01}^2] = \begin{bmatrix} -1 & 1 \\ -1 & 1 \end{bmatrix},$$

$$[O_{10}^2] = \begin{bmatrix} -1 & -1 \\ 1 & 1 \end{bmatrix},\ [O_{11}^2] = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$$

Polynomial basis operators of (3×3) are

$$[O_{00}^3] = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix},\ [O_{01}^3] = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix},$$

$$[O_{02}^3] = \begin{bmatrix} 1 & -2 & 1 \\ 1 & -2 & 1 \\ 1 & -2 & 1 \end{bmatrix},\ [O_{10}^3] = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix},$$

$$[O_{11}^3] = \begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix},\ [O_{12}^3] = \begin{bmatrix} -1 & 2 & -1 \\ 0 & 0 & 0 \\ 1 & -2 & 1 \end{bmatrix},$$

$$\left[O_{20}^{3}\right]=\begin{bmatrix}1 & 1 & 1\\ -2 & -2 & -2\\ 1 & 0 & 1\end{bmatrix},\left[O_{21}^{3}\right]=\begin{bmatrix}-1 & 0 & 1\\ 2 & 0 & -2\\ -1 & 0 & 1\end{bmatrix},$$

$$\left[O_{22}^{3}\right]=\begin{bmatrix}1 & -2 & 1\\ -2 & 4 & -2\\ 1 & -2 & 1\end{bmatrix}$$

It is also proved that the set of $n\times n$ ($n\geq 2$) polynomial operators forms a basis, i.e it is complete and linearly independent.

The following symmetric finite differences for estimating partial derivatives at *(x,y)* position of the gray level image *I* are analogous to the eight finite difference operators O_{ij}s excluding O_{oo}.

$$\frac{\partial I}{\partial y}\Big|x,y=\sum_{i=-1}^{1}[I(x-i,y+1)-I(x-i,y-1)]$$

$$\frac{\partial I}{\partial x}\Big|x,y=\sum_{i=-1}^{1}[I(x+1,y-i)-I(x-1,y-i)]$$

$$\frac{\partial^2 I}{\partial y^2}\Big|x,y=\sum_{i=-1}^{1}[I(x-i,y-1)-2I(x-i,y)+I(x-i,y+1)]$$

$$\frac{\partial^2 I}{\partial x^2}\Big|x,y=\sum_{i=-1}^{1}[I(x-1,y-i)-2I(x,y-i)+I(x+1,y-i)] \quad (7)$$

and so on.

In general,

$$\frac{\partial^{i+j}}{\partial x^i\partial y^j}=\left|O_{ij}\right| \text{ and}$$

$$\frac{\partial^{i+j} I}{\partial x^i\partial y^j}=(\left|O_{ij}\right|,\left|I\right|)=\beta_{ij}', \quad 0\leq i.j\leq 2 \quad i=j\neq 0 \qquad (8)$$

where | | indicates the arrangement in dictionary sequence and (,) indicates the inner product and β_{ij}' are the coefficients of the linear transformations defined as follows.

$$|\beta_{ij}'|=|\boldsymbol{M}|^{t}|I| \qquad (9)$$

where $|\boldsymbol{M}|$ is the 2-D point – spread operator defined as $|\boldsymbol{M}| = |M| \otimes |M|$

The orthogonal transformation defined by the orthogonal system is $|\boldsymbol{M}|$ complete. An orthogonal system $|\boldsymbol{H}|$ by normalizing $|\boldsymbol{M}|$ is obtained as follows

$$\left|H\right|=\left|M\right|(\left|M\right|^{t}\left|M\right|)^{-\frac{1}{2}}$$

Consider the following orthogonal transformations

$$\left|Z\right|=\left|H\right|^{t}\left|I\right|=(\left|M\right|^{t}\left|M\right|)^{-\frac{1}{2}}\left|M\right|^{t}\left|I\right|=(\left|M\right|^{t}\left|M\right|)^{-\frac{1}{2}}\left|\beta'\right| \qquad (10)$$

Since $|\boldsymbol{H}|$ is unitary,

$$\left|I\right|=\left|H\right|\left|Z\right|=\left|M\right|\left|\beta\right|=\sum_{i=0}^{2}\sum_{j=0}^{2}\beta_{ij}\left|O_{ij}\right| \qquad (11)$$

where $\left|\beta\right|=(\left|M\right|^{t}\left|M\right|)^{-1}\left|\beta'\right|$

As per equation (11), the image region $|I|$ can be expressed as a linear combination of the 9 basis operators of which $|O_{oo}|$ is the local averaging operator and the remaining 8 are finite difference operators. From this the completeness relation or Bessel's equality is obtained as follows.

$$(\left|I\right|,\left|I\right|)=(\left|Z\right|,\left|Z\right|) i.e., \sum_{i=0}^{2}\sum_{j=0}^{2}I_{ij}^{2}=\sum_{i=0}^{2}\sum_{j=0}^{2}Z_{ij}^{2}$$

4. EDGE SEGMENTATION BASED ON ORTHOGONAL POLYNOMIALS

In this section, an edge detection method based on identifying the zero crossing in the second directional derivatives of the image is proposed for monochrome images. After detecting the edges, the scan line algorithm is applied to segment the foreground and background region for the proposed encoder of the medical image. The computational approach for detection of zero-crossing in the second directional derivative by using the proposed polynomials operator is presented. Let the image function be *I(x, y)*, then the first order derivative is given by,

$$I'(x,y)\big|_{\theta}=\frac{\partial I}{\partial x}sin\theta+\frac{\partial I}{\partial y}cos\theta \qquad (12)$$

and the second directional derivative is given by

$$I''(x,y)\big|_{\theta}=\frac{\partial^2 I}{\partial x^2}sin^2\theta+2\frac{\partial^2 I}{\partial x\partial y}sin\theta cos\theta+\frac{\partial^2 I}{\partial y^2}cos^2\theta \quad (13)$$

where $\theta=tan^{-1}\left(\frac{\frac{\partial}{\partial y}}{\frac{\partial}{\partial x}}\right)$

Using equation (8), we obtain

$$I_{\theta}''=\beta_{20}'sin^2\theta+\beta_{02}'cos^2\theta+2\beta_{11}'sin\theta cos\theta \qquad (14)$$

Finally, the expression for the second directional derivative in terms of the proposed difference operator becomes,

$$I_{\theta}''(x,y)=\frac{\beta_{20}'\beta_{01}'^{2}+\beta_{10}'^{2}+2\beta_{01}'\beta_{10}'\beta_{11}'}{\beta_{01}'^{2}+\beta_{10}'^{2}} \qquad (15)$$

An edge point can be concluded if the image region under analysis has sufficient gradient and its second directional derivative has a negative slope i.e., a zero crossing. The algorithm for detection of edges in medical images by using this method is given below:

Algorithm: Edge detection using modified zero crossing algorithm

Input : Medical image of size *(image_width* $\times$ *image_height)*
Output: Edge detected image
Steps:
Begin
1. Repeat i[th] loop from 0 to *image_width* do
   begin
   Repeat j[th] loop from 0 to *image_heigh)* do
   begin
2. Extract a (3 $\times$ 3) block [*I*] centred at *(i+1,j+1)*
3. Compute $[\beta'] = [M]^T [I][M]$ where $[M] = \begin{vmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{vmatrix}$
4. Estimate the gradient $I' = (\beta'^2_{01} + \beta''^2_{10})^{\frac{1}{2}}$
5. If (gradient $I' > T$) go to end
6. Compute second directional derivative, I''

$$I''_\theta(x,y) = \frac{\beta'_{20}\beta'^2_{01} + \beta'_{02}\beta'^2_{10} + 2\beta'_{01}\beta'_{10}\beta'_{11}}{\beta'^2_{01} + \beta'^2_{10}}$$

7. If (I''<0) mark the edge point at *(i+1, j+1)*.
   end
   end

End

Once the edge points are identified with the proposed zero crossing algorithm the resultant image is denoted as a two dimensional matrix *E* of size *(image_width* $\times$ *image_height)*. The scan line algorithm is then applied in both horizontal and vertical direction and the results are combined to get the foreground and background medical image region. The horizontal scanning starts from left (value 0) to right (value *image_width*) to find the non-zero value in $E_{i,j}$ and set the column value *j* as the starting column *k*. Next, scans the matrix *E* from right (*image_width*) to left (0) to find the right most edge pixel and set the j^{th} ending column value as *l*. Then fill the line from $E_{i,k}$ to $E_{i,l}$ with value 1 and this iteration is repeated for all the rows in the image to get the horizontal filled image. The similar procedure is applied from top to bottom with values from 0 to *image_height* and the vertical filled image is obtained. Both the horizontal and vertical image is then combined by logical AND operation and the resultant binary image is obtained with foreground regions denoted by 1 and background region denoted by 0.

5. PROPOSED LOSSY TO LOSSLESS MEDICAL IMAGE CODING BASED ON ORTHOGONAL POLYNOMIALS

The input medical image to be coded is divided into non overlapping blocks of size ($n \times n$) and is classified as foreground region, if 50% or above the ($n \times n$) pixel values are identified as 1 in matching with the corresponding binary image otherwise it is classified as background region. Once the image region ($n \times n$) is classified, the orthogonal polynomials based transform coder is applied to encode the foreground region in lossless mode and background region in lossy mode with different quantization levels. The image region ($n \times n$) is applied with orthogonal polynomials based transformation(OPT) as described in section II and the transformed coefficients are quantized using a quantization matrix whose formula, as in JPEG is given below:

$$\text{Quantized value(i, j)=round}\left[\frac{OPT(i,j)}{Quantum(i,j)}\right] \quad (16)$$

where $OPT(i,j)$ is transform coefficient matrix obtained with the orthogonal polynomials transformation. The quantum value matrix $Quantum(i,j)$ is obtained through an integer, called *quality_factor*. Depending upon the requirement of the quality of reconstructed image vis-à-vis compression ratio, the *quality_factor* can be made adaptive and be specified by the user. The relationship between $Quantum(i,j)$ and the *quality_factor* is $Quantum(i,j)$ =1+((1+*i*+*j***quality_factor*). The *quality_factor* which is a user input is generally in the range 1 to 25, and specifies the quantum value, for every element position in the original polynomial transform coefficient matrix. The *quality_factor* is chosen in such a way that it can discard higher frequency coefficients elegantly. That is, when the quality is high, the quantum value corresponding to the higher frequency coefficient sample positions shall be high so that the quantized value can be zero. Thus the quantum value indicates what that the step size is going to be for an element in the complete rendition of the picture, with values ranging from 1 to 25.

For encoding the foreground region, the *quality_factor* value is chosen as 1 which encodes the image in lossless mode and gives perfect reconstruction of the image. Similarly for encoding the background region, the *quality_factor* ranges from 2 to 25 which encodes the image in lossy mode giving higher compression ratio with significant reduction in reconstructed image quality. The quantized transformed coefficients of both regions are then subjected to entropy encoding using variable length coding. For this purpose, the quantized transform coefficients are reordered using zigzag scanning to form a 1D sequence. Due to the fact that DC coefficients of the proposed orthogonal polynomials based coding have high magnitude and the DC values of neighboring blocks are not differing substantially, the DC values are subjected to difference pulse code modulation (DPCM). The first element of the zigzag sequence represents the difference pulse code modulated DC value and among the remaining AC coefficients, the non-zero AC coefficients are huffman coded using variable length code (VLC) that defines the value of the coefficient and the number of preceding zeros. Standard VLC tables specified in the JPEG baseline system are used for this purpose. The side information bit as 0 for foreground region and 1 for background region is sent along with encoded bitstreams. Since the huffman coded binary sequences are instantaneous and uniquely decodable, the compressed image can be decompressed easily in a simple look-up table manner. The rearranged array of transform coefficients is reordered into two dimensional block from the one dimensional regenerated zigzag sequence with dequantization, after taking care of DPCM DC coefficients and we reconstruct the sub image under analysis by using the polynomials basis operators as defined in Section 3. The detailed algorithm of proposed lossy to lossless image coder is described hereunder:

Algorithm for proposed lossy to lossless image coder based on orthogonal polynomials (*LLICOPT*):
Input : Medical image and corresponding binary image.
Output Encoded image with proposed *LLICOPT*.

Steps:

1. Partition the input image into ($n \times n$) blocks and classify it either as foreground region or background region as described in this section.
2. Compute the orthogonal polynomials transformed coefficients as $|\beta'_{ij}| = (|M| \otimes |M|)^t \; |I|$ as descried in section 2.
3. Quantize the transformed coefficients with *quality_factor* value as 1 if the region is classified as foreground region, otherwise encode the background region with *quality_factor* value ranges from 2 to 25 as user input as given in equation (16).
4. Rearrange the quantized transformed coefficients in one dimensional sequence using zig-zag scanning.
5. Encode the DC coefficient using DPCM coder and the remaining AC coefficients using huffman coder.
6. Repeat the above process until all the blocks in the input image have been encoded.

Decoding is the reverse process of encoding and is done as a simple look up table manner. First entropy decoding is applied on the compressed bit streams and the results are multiplied with different quantum values for de-quantizing the foreground region and background region separately along with the side information. The inverse transform is then applied with orthogonal polynomials basis operator as described in section 3 and the reconstructed image is obtained.

6. MEASURE OF PERFORMANCE

The performance of the proposed lossy to lossless medical image coding algorithm is reported by computing the peak signal-to-noise ratio (PSNR), as

$$PSNR = 10 \log_{10} \left[\frac{255^2}{{e_{ms}}^2} \right] \tag{17}$$

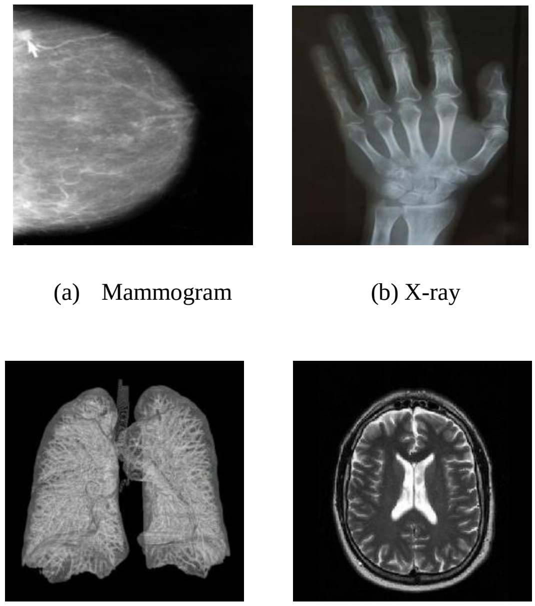
where the average mean-square error e_{ms}, is a very useful measure as it gives an average value of the energy lost in the lossy compression of the original image and is given by

$$e_{ms}^2 = \frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} \left(f(i,j) - g(i,j) \right)^2 \tag{18}$$

where $f(i,j)$ and $g(i,j)$ represent the original and reproduced color images of size ($N \times M$) respectively. The PSNR is measured in decibels (dB).

7. EXPERIMENTS AND RESULTS

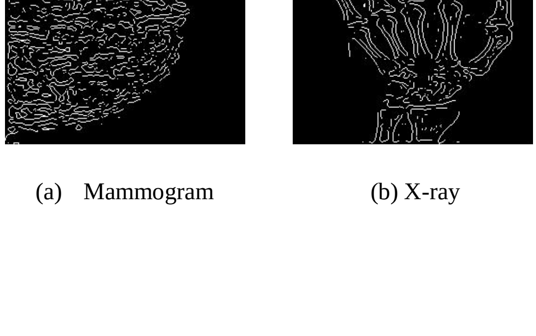
The proposed algorithm has been tested with more than 200 medical images of different kinds such as mammogram, X-ray, CT-scan and MRI images. Some sample medical images which are of size (256×256) with pixel values in the range (0-255) are shown in fig.1.(a)-(d). The image are applied with the proposed orthogonal polynomials based modified zero-crossing edge detection algorithm as described in section 4 and the outputs are presented in fig.2.(a)-(d) corresponding to the original images in fig.1.(a)-d) respectively. The binary imaged with foreground and background region are obtained using scan filling algorithm. Then the foreground regions are encoded losslessly and background regions are encoded in lossy way with the proposed orthogonal polynomials based transform coder as described in section 5. For foreground region, the *quality_factor* is set as 1 and for background region the *quality_factor* ranges from 2 to 25 and the results are presented in table 1. For a $quality\_factor$ 2, the proposed *LLICOPT* coding scheme gives a compression ratio of 66.34% with a PSNR of 46.76dB for the mammogram image. For the same $quality\_factor$, the proposed coding achieves a compression ratio of 64.39% with a PSNR value of 47.50dB for the X-ray image. For the $quality\_factor$ value of 5, proposed *LLICOPT* coding achieves a compression ratio of 73.95% with a PSNR value 45.22dB for mammogram image and 72.78% compression ratio with a PSNR value of 46.33dB for X-ray image. The reconstructed images corresponding to the original images in fig.1.(a)-(d) are presented in fig.3(a)-(d) with the proposed algorithm. For low quality encoding with the $quality\_factor$ of 25, the proposed algorithm achieves a compression ratio of 85.71% with a PSNR value of 38.70dB for the mammogram image and 82.65% compression ratio with PSNR value of 39.86dB for X-ray image.



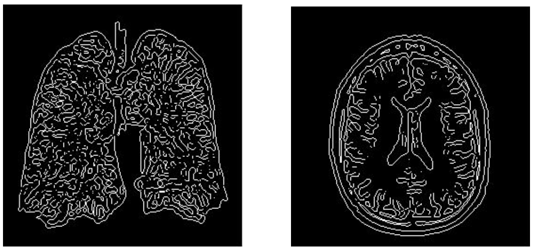
(a) Mammogram (b) X-ray

(c) CT scan (d) MRI image

Figure 1 Original medical test images



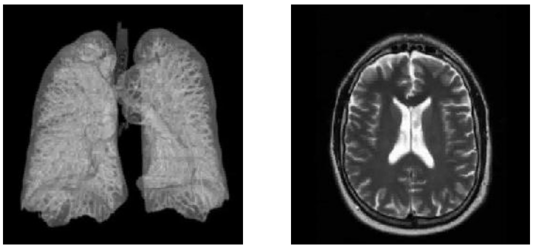
(a) Mammogram (b) X-ray



(c) CT scan (d) MRI image

Figure 2 Edge detection with proposed modified zero crossing algorithm based on orthogonal polynomials.

(a) Mammogram (b) X-ray



(c) CT scan (d) MRI image

Figure 3 Results of proposed coding scheme when *quality_factor* is 5

In order to measure the performance of the proposed technique, the experiments are conducted using DCT based coding scheme and the results are presented in table 2. For a $quality\_factor$ 2, the DCT based coding scheme gives a compression ratio of 57.43% with a PSNR of 44.76dB for the mammogram image. For the same $quality\_factor$, the DCT based coding scheme gives a compression ratio of 55.80% with a PSNR value of 45.54dB for the X-ray image. For the $quality\_factor$ value of 5, DCT based coding scheme gives a compression ratio of 68.55% with a PSNR value 42.22dB for mammogram image and 64.06% compression ratio with a PSNR value of 43.56dB for X-ray image. For low quality encoding with the $quality\_factor$ of 25, the DCT based coding scheme gives a compression ratio of 80.68% with a PSNR value of 36.70dB for the mammogram image and 79.51% compression ratio with PSNR value of 37.61dB for X-ray image.

8. CONCLUSION

In this paper, new medical image coding technique based on orthogonal polynomials is proposed. The edges in the medical images are first detected with the proposed orthogonal polynomials based modified zero crossing algorithm. The critical information in the medical images inside the outer edges are identified as foreground region and the remaining portion are identified as background region using scan filling algorithm. Both regions are encoded using variable quantization with proposed orthogonal polynomials based transform coding technique. Since the discriminate information in the medical images is the foreground region and is encoded losslessly, a hundred percent accuracy is achieved with the proposed technique for diagnosing the problem while at the same time a higher compression ratio is achieved by lossy compression of background region.

Table 6.5 Compression ratio(%) and PSNR(dB) values obtained for various *quality_factor*s with proposed *LLICOPT* algorithm.

QF	**Proposed *LLICOPT* based coding scheme**							
	Mammogram		X-ray		CT-scan		MRI image	
	CR	PSNR	CR	PSNR	CR	PSNR	CR	PSNR
2	66.34	46.76	64.39	47.50	63.01	46.81	67.01	44.86
5	73.95	45.22	72.78	45.33	70.43	45.11	74.89	43.10
10	79.65	43.34	77.32	43.21	73.87	43.07	80.35	42.51
15	81.29	41.95	78.68	42.75	75.07	41.23	82.70	40.63
20	83.44	40.51	80.14	41.08	79.05	40.69	82.53	39.78
25	85.71	38.70	82.65	39.86	81.59	38.42	85.90	37.98

Table 6.6 Compression ratio (%) and PSNR (dB) values obtained for various *quality_factors*(*QF*) with proposed algorithm using DCT based coding scheme.

QF	**Proposed algorithm using DCT based coding scheme**							
	Mammogram		X-ray		CT-scan		MRI image	
	CR	PSNR	CR	PSNR	CR	PSNR	CR	PSNR
2	57.43	44.76	55.80	45.54	56.32	44.02	55.64	45.32
5	68.55	42.22	64.06	43.56	67.67	43.76	64.78	43.12
10	73.90	40.34	72.11	41.94	72.43	42.69	71.86	41.54
15	75.90	39.78	74.61	40.30	74.06	40.18	73.85	40.52
20	77.21	38.51	76.80	39.36	75.23	39.89	75.34	39.13
25	80.68	36.70	79.51	37.61	79.46	37.78	78.67	38.63

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