Projection-Based Medical Image Compression for Telemedicine Applications

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Abstract Recent years have seen great development in the field of medical imaging and telemedicine. Despite the developments in storage and communication technologies, compression of medical data remains challenging. This paper proposes an efficient medical image compression method for telemedicine. The proposed method takes advantage of Radon transform whose basis functions are effective in representing the directional information. The periodic re-ordering of the elements of Radon projections requires minimal interpolation and preserves all of the original image pixel intensities. The dimension-reducing property allows the conversion of 2D processing task to a set of simple 1D task independently on each of the projections. The resultant Radon coefficients are then encoded using set partitioning in hierarchical trees (SPIHT) encoder. Experimental results obtained on a set of medical images demonstrate that the proposed method provides competing performance compared with conventional and state-of-the art compression methods in terms of compression ratio, peak signal-to-noise ratio (PSNR), and computational time.

Keywords Medical image compression · Telemedicine · Radon transform · Projection domain · SPIHT

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Introduction

With the increasing population, affording primary health care to human community is one of the major challenges. Telemedicine is a good solution to reach the unreachable that live in areas with limited medical facilities and personnel [1]. In telemedicine, medical images need to be transmitted conveniently over the network for perusal by another medical expert. The transmission of huge amount of medical data with comparatively low bandwidth is the critical requirement in telemedicine. Hence, the compression of medical images is one of the major challenges to be addressed in telemedicine for efficient transmission [2, 3]. Many advanced image compression methods have been proposed in response to the growing demands for medical images. Among the various compression methods, transform-based methods that convert an image in spatial domain into spectral domain are very effective. In transform-based coding, the transformation process converts a large set of highly correlated pixels into a smaller number of decorrelated transform coefficients. These coefficients are then quantized and entropy encoded. It has been assumed that noise (whitening effect) is independent of spatial coordinates and that it is uncorrelated with respect to the image itself.

For the past two decades, there has been abundant interest on wavelet transform for the compression of medical images [4]. Wavelets are favorable to represent 1D signals with finite number of discontinuities [5]. Although wavelet transform has gained enormous interest for signal processing, it is unable to resolve 2D singularities along arbitrarily shaped curves. Curvelet transform [6] represents 2D functions with smooth curve discontinuities at an optimal rate. It provides nonlinear approximation close to the optimum without explicit knowledge of the image geometry. Although it is desired for compression [7], the discretization of curvelet transform turns out to be challenging and the resulting algorithms are highly

complicated. Contourlet transform [8] uses a discrete filter bank structure to deal effectively with piece-wise smooth images. Even though it is suitable for tasks such as image compression [9] by having lower redundancy and less complexity, it has less clear directional features than curvelet, which in turn leads to artifacts in image compression. Bandelet transform is able to construct orthogonal bases of regular functions. However, the best visual quality is achieved at the expense of substantial increase in the computational complexity [10].

Warped discrete cosine transform [11] determines discrete cosine transform (DCT) samples by warping the frequency axis through an all-pass transform. However, the improved performance is achieved at the increased computational complexity. Ridgelet transform [12] is effective in representing straight line discontinuities but unable to resolve 2D singularities. Ponomarenko et al. [13] proposed an adaptive JPEG-based image compression method. The blocking artifacts can be reduced by using any smoothing filter, but the detailed information in the image will be sacrificed. Chen [14] presented a DCT-based sub-band decomposition method for the compression of medical images. This approach uses transform function to DCT coefficients to concentrate signal energy and a modified set partitioning in hierarchical trees (SPIHT) algorithm to organize data and entropy encoding. Ripplet transform is a higher dimensional generalization of wavelet transform capable of representing images at different scales and different directions. Since ripplet transform localizes the singularities more accurately, it provides relatively good performance on the compression of medical images [15]. Region-based coding [16] is simple to implement, but the blocking artifacts need to be removed using a smoothing filter. Vector quantization [17] achieves compression with good visual quality and relatively high compression ratio. However, the implementation is more complex which acts as a drawback for telemedicine system. Minasyan et al. [18] demonstrated the performance of Haar wavelet for image compression. Even though Haar wavelet has less computational complexity suitable for efficient transmission of images, it does not provide sparse representation of edges in images.

During the past two decades, various encoding methods have been developed to address major challenges faced by medical imaging. The embedded zerotree wavelet (EZW) is an efficient coding scheme developed by Shapiro [19]. It is further extended by Said et al. [20] to give a new scheme called SPIHT which provides even better performance than the other extensions of EZW. SPIHT works with tree structure, called spatial orientation tree which defines the spatial relationships among transformed coefficients in different decomposition sub-bands. It provides salient features such as visually superior quality, intensive progressive capability, SNR scalability, and low computational complexity when compared to other encoders [21].

Radon transform plays an important role in applied mathematics and image processing. It permits exact reconstruction of a discrete object from its discrete projections. Placidi [22] proposed a compression algorithm for medical images based on projections entropy calculation. The algorithm is based on the evaluation of the information content of a given image through the calculation of a function that is identical to the entropy defined in thermodynamics. The entropy is not calculated directly on the original image but on its projections. Hu et al. [23] have compared the class of linear operators, which contains Radon, Bessel, and Riesz fractional integration transforms to deal with the inverse problem of the Radon transform and receive more effective reconstruction. Dong et al. [24] have proposed a method that uses the analysis-based approach of wavelet frame method and Radon domain inpainting mechanism to reconstruct high-quality images with very small number of projections. Radon-based rotations require minimal interpolation and preserve all of the original image pixel intensities [25].

Among the proposed compression methods, much attention has been given on resolving 2D singularities and achieving the desirable characteristics such as high peak signal-to-noise ratio (PSNR), and little work has been done on efficient representation of directional information of a signal. Grounded on this motivation, this paper proposes a compression method for medical images using Radon transform whose basis functions are effective in representing the directional information. Specifically, the proposed method employs discrete Radon transform (DRT) [26, 27] and SPIHT encoder [20] to compress the medical images and to provide efficient representation of images. In DRT, the set of projection angles is intrinsic to each image array size. The periodic re-ordering of the elements of the Radon projections requires minimal interpolation and preserves all of the original image pixel intensities. Many researchers have proven the efficiency of Radon transform for face recognition [28], detection of finger prints [29], generation of unique nanotags for product anti-counterfeiting [30], and extraction of characteristic features of images [31]. Performances of the proposed method are evaluated and compared with conventional and state-of-the-art methods such as DCT, Haar wavelet, contourlet, and curvelet-based compression. Experimental results demonstrate that the proposed method outperforms the existing methods in terms of PSNR, structural similarity index measure (SSIM), compression ratio, and computational time.

Materials and Methods

DRT

DRT represents an image as a collection of projections along various directions. It calculates multiple line integrals of

absorption along parallel paths and repeats the process for a set of different angles of incidence arranged around a circle. It is an effective method to analyze signals between spatial domain and its projection domain. Each coordinate in projection domain becomes a straight line in spatial domain, and contrarily, each coordinate in spatial domain corresponds to a sine curve in projection domain. Since DRT has no nontrivial analog in the 1D space, exact invertibility makes it useful for multidimensional signal processing [27].

The Radon transform operation is depicted in Fig. 1. In the 2D case, the line L_s can be represented uniquely by the parameters s and θ , where θ measures the counterclockwise angle of the line from the vertical, and s measures the distance of the line from the origin of the (x,y) plane. From Fig. 1, the projection of distance s and the vector v in the (x,y) plane are given as

$$s = x \cos \theta + y \sin \theta \quad (1)$$

$$v = -x \sin \theta + y \cos \theta \quad (2)$$

Upon simplification,

$$s \sin \theta + v \cos \theta = y \quad (3)$$

$$s \cos \theta - v \sin \theta = x \quad (4)$$

The Radon transform over integrable region is defined as

$$g(s, \theta) = \int_{-\infty}^{\infty} f(x, y) dv, \quad (x, y) \in L_s \quad (5)$$

Fig. 1 Angle of projection in Radon transform

When substituting the values of x, y in Eq. (5),

$$g(s, \theta) = \int_{-\infty}^{\infty} f(s \cos \theta - v \sin \theta, s \sin \theta + v \cos \theta) dv \quad (6)$$

The Radon operator maps the function $f(x, y)$ to a function $g(s, \theta)$, where $g(s, \theta)$ is the line integral of $f(x, y)$ over the line defined by s and θ . Hence, the Radon transform of a function $f(x, y)$ is given by $g(s, \theta)$, $g(s, \theta)$

$$= \Delta \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \delta(x \cos \theta + y \sin \theta - s) dx dy \quad (7)$$

where δ is the Dirac function, s denotes the perpendicular distance of the line from the origin, and $\theta \in [0, \pi]$. The dimension-reducing property allows the conversion of 2D signal $f(x, y)$ to a set of simple 1D signal independently on each of the projections. In general, increasing the number of projections and increasing the number of points measured on each projection improve image quality with reduced artifacts.

Medical Image Compression Using Proposed Method

In the proposed image compression method, the input medical image $f(x, y)$ is first applied to discrete Radon transform which maps the spatial domain coordinates (x, y) to projection domain coordinates (s, θ) . Applying Radon transform for a given set of angles computes the projection of the image along the given angles. It converts the line integrals into a related set of projections at right angles to the original beams. The technique computes Radon projections in different orientations and captures the directional features of the input image.

The Radon transform of a function $f(x, y)$ is given by $g(s, \theta)$

$$g(s, \theta) \triangleq \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \delta(x \cos \theta + y \sin \theta - s) dx dy$$

where δ is the Dirac function and $s \in (-\infty, +\infty)$ and $\theta \in [0, \pi]$.

This transform preserves the variations in pixel intensities. While computing Radon projections, the pixel intensities along a line are added. This process improves the spatial frequency components in a direction in which Radon projection is computed. When features are extracted using Radon transform, the variations in the spatial frequency are not only preserved but boosted also.

Now, the transformed coefficients are further coded using SPIHT algorithm which encodes the coefficients by spatial orientation tree. This algorithm organizes the transformed

coefficients into significant and insignificant portions based on the significance function as in Eq. (8).

$$s_n(R) = \begin{cases} 1, & \max |R_{s,\theta}| \geq 2^n \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

where $s_n(R)$ is the significance of a set of coordinates and $R_{s,\theta}$ represents the resultant Radon coefficients. In spatial orientation tree, each coefficient is progressively encoded from most significant bits to least significant bits. The coding starts from highest magnitude coefficients at the lowest pyramids. The SPIHT encoding makes use of three sets of lists based on the significance of coefficients: (i) the list of insignificant pixels (LIP), (ii) the list of insignificant sets (LIS), and (iii) the list of significant pixels (LSP). LIP and LSP contain nodes with single pixels and LIS consists of nodes with descendants. This algorithm utilizes two stages of operation: sorting and refinement stages. The maximum number of bits needed to represent the highest coefficients in the spatial orientation tree is obtained and expressed as $n_{\max}$, where $n_{\max} = \lfloor \log_2(\max |R_{s,\theta}|) \rfloor$.

During the sorting stage, the pixels in LIP are tested for $n_{\max}$, and the significant result of $s_n(R)$ is transferred to the output. Significant pixels in LIP are transferred to LSP. Each set of pixels in LIS is also evaluated based on significance test. If the set is observed as significant, then it is removed from the list and portioned into subsets. If the subsets with single coefficient are observed to be significant, they will be transferred to LSP or else they will be included in LIP. LSP now consists of pixel coordinates that are inspected in the refinement stage which produces the n^{th} most significant bit of $s_n(R)$. The value of n is decreased by 1, and the above-

mentioned sorting and refinement procedures are repeated until all the transformed coefficients are evaluated completely.

The procedure may be summarized as follows:

- Step 1 Input the medical image $f(x,y)$ of size 256×256 , 8 bpp.
- Step 2 Compute the projection of distance s and vector v in the given plane.
- Step 3 Apply discrete Radon transform to map the spatial domain coordinates (x,y) to projection domain coordinates $g(s,\theta)$

$$g(s, \theta) = \int_{-\infty}^{\infty} f(x, y) dv, \quad (x, y) \in L_s$$

$$g(s, \theta) \triangleq \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \delta(x \cos \theta + y \sin \theta - s) dx dy$$

- Step 4 Encode the resulting Radon coefficients using SPIHT encoder.
- Step 5 Measure the resulting image quality in terms of PSNR (dB), SSIM, compression ratio, and computational time (s).

Experimental Results and Discussions

The performances of the proposed method are evaluated on a set of medical images of size 256×256 , 8 bits/pixel, and the quality of compressed images has been assessed in terms of

Fig. 2 a–g Set of medical images used for evaluation

PSNR (dB), bitrate (bpp), SSIM, compression ratio, and computational time (s). The test medical image set is shown in

Fig. 2a–g. The efficiency of the proposed method is evaluated on comparison with DCT [14], Haar wavelet [18], contourlet

Fig. 3 PSNR (dB) achieved for test images using different methods. **a** T1 WI-MRI ankle. **b** T2WI-axial-1 view of brain. **c** T2WI-axial-2 view of brain. **d** T1-weighted MRI lungs. **e** MRI abdomen. **f** CT axial view of pancreas. **g** Sagittal stir axial view of head

(d) T1-weighted MRI Lungs

(e) MRI Abdomen

(f) CT-axial view of Pancreas

Fig. 3 (continued)

Fig. 3 (continued)

[9], and curvelet [7]-based compression methods, encoded using SPIHT encoder. In Haar wavelet transform and curvelet transform, the input image is decomposed into three levels based on 2D wavelet transform. Coefficients in all the high-frequency sub-bands are selected for further processing. Contourlet transform is constructed via filter banks and can be viewed as an extension of wavelets with directionality. For implementation, it utilizes Laplacian pyramid to capture the point discontinuities and directional filter banks to link the point discontinuities into linear structures.

In order to implement and analyze the proposed and existing compression methods, the image processing toolbox of MATLAB software is used. All the algorithms are executed on a general personal computer with Intel(R) i5 processor at 2.67 GHz with 4 GB RAM. The following subsections present thorough experimental investigations of the overall behavior of the proposed method. “Evaluation of Image Quality Based on PSNR” section analyzes the image quality of the proposed and existing methods in terms of PSNR, and “Evaluation of Image Quality Based on SSIM” section evaluates the image quality in terms of SSIM. “Evaluation of Compression Ratio” section tabulates and analyzes the compression ratio and bitrates achieved by the proposed and existing methods. “Evaluation of Computational Time” section analyzes the computational time utilized by the proposed and existing methods for the compression of medical images. The subjective evaluations on the diagnostic quality of compressed images are presented in “Evaluation of Image Quality Based on Subjective Assessment” section. Finally, “Computational Complexity Considerations” section describes the computational complexity of the proposed and existing methods.

Evaluation of Image Quality Based on PSNR

The major design objective of compression method is to obtain the best visual quality with minimum bit utilization. PSNR is one of the most adequate parameters to measure the quality of compression. If the PSNR values are higher, the quality of compression is better and vice versa. It is defined as

$$\text{PSNR} = 10 \times \log_{10} \left(\frac{255^2}{\text{MSE}} \right) \quad (9)$$

MSE in Eq. (9) represents the mean square error of the image and is defined as

$$\text{MSE} = \frac{1}{M \times N} \times \left[\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (f(x,y) - F(x,y))^2 \right] \quad (10)$$

where $M \times N$ represents the size of the image, $f(x,y)$ denotes the original image, and $F(x,y)$ denotes the compressed image. Bitrate (bpp) is defined as the ratio of the size of the compressed image in bits to the total number of pixels.

It is observed from Fig. 3a–g that the proposed method exhibits relatively high performance in terms of PSNR. This is due to the fact that the periodic re-ordering of the elements of Radon projections requires minimal interpolation and preserves all of the original image pixel intensities. Contourlet transform utilizes Laplacian pyramid to capture point discontinuities. In addition, it uses directional filter banks to relate point discontinuities into linear structures. However, the non-sub-sampled process in contourlet transform causes frequency

Fig. 4 SSIM values for the test images at various bitrates using different methods. **a** T1WI-MRI ankle. **b** T2WI-axial-1 view of brain. **c** T2WI-axial-2 view of brain. **d** T1-weighted MRI lungs. **e** MRI abdomen. **f** CT axial view of pancreas. **g** Sagittal stir axial view of head

aliasing, which leads to relatively low PSNR. In Haar wavelet transform, the lack of translation invariance and poor energy

compaction yield relatively low PSNR. DCT also suffers from blocking artifacts caused by discontinuities. Owing to these

Fig. 4 (continued)

drawbacks, the PSNR achieved by the reference methods are relatively low. Since Radon transform preserves the deviations in pixel intensities, it achieves relatively high PSNR compared to existing methods.

Evaluation of Image Quality Based on SSIM

The SSIM is an objective image quality metric used to measure the similarity between two images based on the

Fig. 4 (continued)

characteristics of human visual system. It measures the structural similarity rather than error visibility between two images. SSIM is defined as

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (11)$$

where x and y represent spatial patches, and μ_x and μ_y are the mean intensity values of x and y , respectively. σ_x^2 and σ_y^2 denote standard deviation of x and y , respectively, and C_1 and C_2 are constants. In Eq. (11), SSIM (x, y)

is equal to unity if and only if $x=y$. The mean intensity and standard deviations are calculated by Eqs. (12–14) and (14–16) as follows:

$$\mu_x = \frac{1}{M \cdot N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [x(i, j)] \quad (12)$$

$$\mu_y = \frac{1}{M \cdot N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [y(i, j)] \quad (13)$$

Table 1 Compression ratios and bitrates (bpp) of medical images using proposed and existing compression methods

Medical images 256×256:8	Compression methods				
	DCT-SPIHT	Haar-SPIHT	Contourlet-SPIHT	Curvelet-SPIHT	Radon-SPIHT (proposed)
T1WI-MRI ankle	13.52:1 (0.59 bpp)	11.07:1 (0.72 bpp)	12.82:1 (0.62 bpp)	12.55:1 (0.63 bpp)	16.52:1 (0.48 bpp)
T2WI-axial-1 view of brain	13.15:1 (0.6 bpp)	13.41:1 (0.59 bpp)	12.53:1 (0.64 bpp)	10.88:1 (0.73 bpp)	15.15:1 (0.53 bpp)
T2WI-axial-2 view of brain	13.21:1 (0.61 bpp)	11.92:1 (0.67 bpp)	12.98:1 (0.62 bpp)	11.96:1 (0.67 bpp)	13.8:1 (0.58 bpp)
T1-weighted MRI lungs	9.45:1 (0.85 bpp)	9.62:1 (0.83 bpp)	10.28:1 (0.78 bpp)	10.59:1 (0.76 bpp)	10.54:1 (0.76 bpp)
MRI abdomen	10.78:1 (0.74 bpp)	12.44:1 (0.64 bpp)	10.86:1 (0.74 bpp)	11.84:1 (0.68 bpp)	10.3:1 (0.78 bpp)
CT axial view of pancreas	6.23:1 (1.28 bpp)	9.92:1 (0.81 bpp)	9.83:1 (0.81 bpp)	10.12:1 (0.79 bpp)	11.07:1 (0.72 bpp)
Sagittal stir axial view of head	13.92:1 (0.57 bpp)	12.22:1 (0.65 bpp)	12.48:1 (0.64 bpp)	12.26:1 (0.65 bpp)	15.22:1 (0.51 bpp)

Bold values indicate the high compression ratio achieved by the compression methods

$$\sigma_x = \left[\frac{1}{M \cdot N - 1} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [x(i, j) - \mu_x]^2 \right]^{\frac{1}{2}} \quad (14)$$

$$\sigma_y = \left[\frac{1}{M \cdot N - 1} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [y(i, j) - \mu_y]^2 \right]^{\frac{1}{2}} \quad (15)$$

$$\sigma_{xy} = \left[\frac{1}{M \cdot N - 1} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [x(i, j) - \mu_x] [y(i, j) - \mu_y] \right]^{\frac{1}{2}} \quad (16)$$

In Eq. (11), C_1 and C_2 are added to avoid instability when $\mu_x^2 + \mu_y^2$ or $\sigma_x^2 + \sigma_y^2$ are very close to zero. These constants can be adjusted by $C_1 = (K_1 L)^2$ and $C_2 = (K_2 L)^2$, where K_1 and K_2 are small constants and L denotes the dynamic range of pixel values. In this work, K_1 is set to 0.01 and K_2 is set to 0.03. Since 8-bit gray level images are used in this work, $L = 255$.

From Fig. 4a–g, it is inferred that the proposed method yields better SSIM value (close to 1) than existing methods. This is due to the fact that the tunable redundancy of Radon transform distributes the data over a predefined projection set and exploits both the periodicity within the each projection and the similarities between projections. Haar wavelets are efficient in representing point singularities. However, they are unable to provide effective representation of higher dimensional singularities due to their poor orientation selectivity. Contourlet transform is capable of providing flexible number of directions and able to capture the inherent geometrical structure of images. However, the combination of directional filter with the Laplacian pyramid

Fig. 5 Comparison of computational time (s) required for proposed and existing methods

results in pseudo-Gibbs phenomena around the singularities. Even though curvelet transform provides optimally sparse representations of object, it is inadequate in exhibiting discontinuity along the curve with bounded variation functions. Similarly, DCT also suffers from block-shaped artifacts near edge regions in images. Therefore, the reference methods achieve relatively low SSIM when compared to the proposed method.

Evaluation of Compression Ratio

Compression ratio enumerates the reduction in image size yielded by the compression method. It is calculated as the number of bits occupied by each pixel before compression,

Fig. 6 a–c Visual quality comparisons of Radon transform-based compression of test images. *i* Original image. *ii* Compressed image

Table 2 Subjective evaluations of diagnostic quality of medical images using the proposed compression method

Evaluation parameters	Medical images used for evaluation				
	T2WI-axial-1 view of brain Excellent/good/average/poor	T1-weighted MRI lungs	MRI abdomen	CT axial view of pancreas	T1WI-ankle
Visual quality of the image	Excellent	Excellent	Excellent	Excellent	Excellent
Representation of edges in images	Excellent	Excellent	Good	Excellent	Excellent
Image sharpness	Excellent	Excellent	Excellent	Excellent	Good
Image contrast	Excellent	Excellent	Excellent	Excellent	Excellent
Able to view the difference between bone and soft tissue	Excellent	Good	Excellent	Excellent	Excellent
Able to view the difference between air and water	Excellent	Excellent	Excellent	Excellent	Excellent
Image sharpness of soft tissue window	Excellent	Excellent	Excellent	Excellent	Good

divided by the number of bits occupied per pixel after compression. For a gray scale image, compression ratio = $(1/\text{bpp}) \times 8$. Table 1 tabulates the compression ratios and bitrates (bpp) of the proposed compression using Radon transform and the existing methods.

It is inferred from Table 1 that the proposed method outperforms existing methods on the compression of T1WI-MRI ankle, T2WI-axial-1 view of brain, T2WI-axial-2 view of brain, CT axial view of pancreas, and sagittal stir axial view of head. The dimension-reducing property of Radon transform results in less number of significant coefficients, thus yielding higher compression ratio. However, for T1-weighted MRI lungs, curvelet-based method performs good because it approximates images from coarse to fine resolutions. For MRI abdomen, Haar wavelet performs better because the approximation component contains most of the energy and the coefficients are reduced with input permutation of variables. From Table 1, it is understood that the average compression ratio achieved by the proposed method is 13.22. It outperforms DCT by 15.35 %, Haar wavelet by 14.85 %, contourlet-based method by 13.18 %, and curvelet-based method by 15.45 %.

Evaluation of Computational Time

The computational time depends on the complexity of the compression algorithm, the efficiency of the

implementation of algorithm, and the speed of the processor hardware. All the methods are executed on a general personal computer with Intel(R) i5 processor at 2.67 GHz with 4 GB RAM. Figure 5 illustrates the result obtained for proposed and existing methods for different medical images in terms of computational time (s) with file size (KB). The average computational time spent on this processor to compress the given medical image using the proposed method is 0.36 s, whereas in the case of DCT, it is 0.48 s, and in Haar wavelet, it is 0.45 s. Contourlet takes 0.52 s and curvelet takes 0.72 s to compress the data. Since Radon transform removes the need for interpolation and gives the minimum number of projections required, the computational time is relatively low when compared to the existing methods.

Evaluation of Image Quality Based on Subjective Assessment

The main objective of the proposed compression method is to reproduce images with no visible distortions. In order to analyze the visual quality of compressed medical images, an extensive subjective evaluation was carried out by cardiac radiologists on the following evaluation parameters, viz. visual quality of the image, representation of edges in images, image sharpness, image contrast, ability to view the difference between bone

Table 3 Subjective evaluations of artifacts levels of medical images using the proposed compression method

Evaluation parameters	Medical images used for evaluation				
	T2WI-axial-1 view of brain None/mild/moderate/severe	T1-weighted MRI lungs	MRI abdomen	CT axial view of pancreas	T1WI-ankle
Appearance of artifacts	None	None	None	None	None
Vignetting (darkens near the corners)	None	None	None	None	None
Visible distortion of information signal	None	None	None	None	None

and soft tissue, ability to view the difference between air and water, image sharpness of soft tissue window, appearance of artifacts, vignetting, and visible distortion of information signal.

The rating scale is categorized into four equal regions given with adjectives “excellent” (extremely or desirable high quality), “good” (high quality), “average” (acceptable quality), and “poor” (poor quality). The appearance of artifacts level is also analyzed. The distortion level is divided into “none,” “mild,” “moderate,” and “severe.” Figure 6 shows the visual quality comparisons of original and compressed images using the proposed method. Tables 2 and 3 show the subjective evaluations of diagnostic quality of medical images using the proposed method. The result of subjective assessment reveals that most of the images are rated as excellent and not a single image has failed the test of acceptability. The proposed method preserves the diagnostic quality of medical images efficiently, and the differences between bone and soft tissue are visible clearly.

Computational Complexity Considerations

The experimental result section is concluded with a brief discussion regarding the complexity of the proposed and existing methods. The proposed method is computationally attractive because Radon transform requires exactly n^3 additions and n^2 multiplications for n histograms. The implementation of contourlet transform is based on pyramidal band-pass decomposition and multiresolution directional filtering stages. Hence, contourlet transform has a complexity of $O(n)$ for $n \times n$ image. The computational complexity of DCT and Haar wavelet methods is $O(n \log(n))$ and of $O(\log_2(n))$, respectively. Curvelet transform has relatively high complexity, since it runs in $O(n^2 \log n)$ flops for an $n \times n$ image.

Conclusions

Medical image compression using Radon transform, which provides efficient representation of directional information, has been proposed. The Radon transform computes projections of the image. The periodic re-ordering of the elements of Radon projections requires minimal interpolation and preserves all of the original image pixel intensities. The resultant Radon coefficients are then encoded using SPIHT encoder. Application of the proposed compression method to experimental medical images demonstrates its relatively better performance in terms of compression ratio, PSNR, SSIM, and computational time.

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