Energy Interpolated Mapping for Image Compression with Hierarchical Coding

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Abstract

Objectives: To achieve high compression rate by reducing the more redundant information in medical images. More compression rate results in less resource utilization and also reduces the processing overhead and time consumption.

Methods/Statistical Analysis: In this approach, initially the medical image was decomposed through multiwavelet transform. Then a band selection procedure is performed on the obtained sub bands to select the bands which are non-correlated. Thus, the redundant information existing in the bands will be reduced. Then, the selected bands were processed for energy based interpolation to select the features which are more informative and also to reduce the redundant information further. Next, the hierarchical coding was applied over the obtained features.

Findings: Simulation results are carried out over various medical images and for every image, the quality was checked through PSNR and the performance was checked through processing overhead and computation time (sec). Compared with earlier approaches, the processing overhead of proposed approach observed to be less and the computation time also. Similar, the PSNR is observed to be high and MSE as low.

Applications/Improvements: The proposed medical image coding system will be used in telemedicine applications where there is a need of efficient resource utilization to transmit the data with fewer resources.

Keywords: Band Selection, Computation Time, Energy Interpolated Features, Hierarchical Coding, Medical Image Compression, , PSNR, Processing Overhead,

1. Introduction

In recent days, due to the wide development in the heterogeneous services in image and video oriented applications, the applications related to image/video coding will becoming limited due to the limitation on the available resources. The conventional approaches based on multi-bit stream are limited in the case of heterogeneity issue and insufficient for the applications based on multi-bit rate. In multi-bit stream coding, the image will be decoded partially at various quality and resolution levels. In earlier, various scalable coding approaches are proposed. However, all the former approaches have limited decoding properties. The rapid development in the imaging technology has led to new requirements for image compression. Generally, the image compression techniques aims towards the increased quality of reconstructed image under medium-low bit rates and also tries to maintain the quality of image even under decrement of bit rate. The conventional multi-bit stream approaches are becoming inefficient and impractical due to the wide varying resources. The bit level scalable image codecs allow the medical image reconstruction through the procedure of an optimal truncation point in the

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single bit stream. For the analysis of medical image, image browsing, progressive transmission, multimedia oriented applications and transcoding in a compatible manner, in the fashion of multi bit rate digital hierarchy, obtaining the MRI image with optimal quality in an embedded fashion, i.e., proving compatibility to the all encoded bits with the target bit rate is the current facing problem for an engineer. Since the medical images carry most important and huge information, encoding them at very low bit rate will results in the information loss and also gives the low quality medical image reconstruction. If this was viewed through the effect of channel, it will become worse due to the effect of narrow bandwidth. Several approaches are proposed in earlier for encoding the MRI image data before transmission. However, these approaches obtained better results at high bit rates and shown poor results in the case of low bit rates. This problem can be overcome by encoding the Images in such a way that there will be in compatibility for the encoded bits with lower bit rate. Hierarchical coding is one of the coding techniques which perform image coding in a hierarchical fashion by considering the importance of pixels at every stage. In hierarchical coding, the image is initially processed for decomposition through Discrete Wavelet Transform (DWT). DWT decomposes the image into subbands (LL, LH, HL and HH). Then the obtained sub bands are processed for further coding. In DWT, the obtained coefficients represent only few resolution levels which results in poor quality in the reconstructed image. So, to improve the quality of reconstructed image, a new coding technique was proposed based on multiwavelet and a band selection procedure. The Multiwavelet is an extension to the DWT in which the remaining (LH, HL and HH) bands are also processed for further decomposition along with approximation (LL) coefficients to obtain further fine resolution levels. Next, a band selection procedure is carried out over the obtained subbands by measuring inter-correlation between the subbands. The bands with minimum correlation are selected for further encoding. However, the main disadvantage is the computational complexity is observed to be very high and also consumes more time for evaluation.

To overcome the above drawback, in this paper, a new image coding is proposed based on the spectral characteristics of the images. The proposed approach selects the sub bands of multiwavelet transform based on their spectral characteristics for encoding. Since the frequency representation gives more prior information through finer resolutions, the accuracy will be increased. Thus, the proposed approach can be able to recover almost all the information along with reduced complexity. Rest of the paper is organized as follows: section II represents the complete details of earlier medical image coding techniques. Section 3 represents the complete details of earlier approach. The complete details of proposed approach are illustrated in section 4. Performance evaluation is shown in section 5 and finally the conclusion is given in section 6.

2. Past Approaches

This image compression system was developed based on two aspects, zero-tree/block coding and the context modeling of subband coefficients. Zero-tree/block coding clusters the subband/wavelet coefficients by considering their nature of energies both in space and frequency. These coders apply the hierarchical set partitioning method with respect to a threshold to split the significant coefficients in the bit plane coding pass, while preserving the insignificant coefficients. This procedure creates a symbol by coding large region of zero pixels. This method provides an effective method to represent a group of zeros of subband/wavelet coefficients compactly. In this bit plane encoding only a few numbers of coefficients are processed instead of all coefficients. Thus, the processing speed of these approaches is very high. The high efficiency in the compression can be achieved through the context modeling. In this type of coders, an arithmetic coding based on the context was applied on the individual pixel of DWT bit planes. In the context modeling, the strong correlations between the coefficients of same band and also with the other bands are utilized effectively for encoding. Though, there is simplicity in the context modeling, the limited context information is insufficient to predict the current node’s status. Some carefully designed context modeling algorithms outperformed the zero-tree/block coders in performance with respect to PSNR. However, the computational complexity is observed to be very high, because, there is a need to scan the entire subbands at least once to complete the encoding of full bitplane. Here, we propose an efficient image coding technique, embedded medical image coding algorithm using Zero Blocks of subband/ wavelet coefficients and context modeling Embedded Zero Block Coder (EZBC) which was advantageous in both computational complexity and PSNR. In this EZBC, the PSNR will be increased due to the consideration of correlation of
subband coefficients. The main base for the zero block coding is set partitioning. Here, an adaptive quad tree splitting technique SWEET was adopted to split the significant coefficients and also to encode every block of zero pixels\cite{10,11} into one symbol. Initially, the individual bands of DWT\cite{10} coefficients are represented in the quadtree form. The subband/wavelet coefficients\cite{11,12} are placed at the bottom level of quadtree. The maximum intensity of all DWT\cite{11,12} coefficients is placed as a root node at the top of the tree with single node representation. The root node is the only one insignificant at the starting of process. Next, every quadtree is divided into four insignificant nodes of the next lower level once; it tests as a significant over a threshold of present bitplane coding pass. This process is applied recursively on the next level descendant nodes up to the bottom level of quadtree. In this manner, there will be an efficient and compact quick representation is achieved into the high energy regions of all zero pixels. In EZBC, a careful design is carried out to encode the nodes of quadtree at different subbands obtained at different tree levels. Thus, this EZBC attains the both low complexity and compact representation. Here, the zero block coders gives less complexity and the context information is added in an effective way. Here, the zero block represents pixels only form one subband. Thus, the EZBC is applicable to scalable applications inherently. With the aid of interband context, correlation of subband/wavelet coefficients can be utilized still more effectively across various scales without having zero tree spanning.

3. **Multiwavelet Band Selection Coding**

A selective coding\cite{1} was developed for the image compression and a multi-wavelet is used for subband decomposition. In this approach, initially, the image I is decomposed into K subbands by convolving with H_z(k) of the analysis bank. After decimation and expansion by a factor N, the full image is reconstructed through a synthesis filter bank with filters G_k(z) followed by summation. A lowpass FIR filter is used for the derivation of analysis filters of having length L. A cost optimization approach was used for the signal estimation where the subbands are adaptively processed called as Subband Adaptive Filter (SAF). The base for the SAF operation is Least Mean Square (LMS)-adaptive filter. The convergence of such filter is based on the LMS function optimization, wherein the weight functions are used for error optimization. A normalized SAF is proposed for faster convergence of cost function. In NSAF, the number of subband filters is increased to increase the speed of convergence by keeping the error at same steady state level. Though, it offers better results in small length sequences, it is having high computational complexity in the case of extremely long length sequences, for example, the application of acoustic echo cancellation. A dynamic selection based Normalised Spectral Abundance Factor (NSAF) (DS-NSAF) is proposed to overcome this issue with NSAF. DS-NSAF performs a sorting process to select the subband filters dynamically to obtain the faster convergence and uses adaptive filter weight. Figure 1 shows the schematic of the conventional approach.

Since DS-NSAF performs a dynamic selection of subband filters, the Mean Square Deviation (MSDs) are minimized at every iteration. This approach achieved a reduced complexity while maintaining the dynamic selection performance. Though DS-NSAF achieved better results through the dynamic selection of sub bands, it can’t achieve improved performance. Because, the DS-NSAF performs the band selection procedure through the inter band correlation evaluation in the temporal domain only. I.e., the correlation is measured for the amplitudes of sub band coefficients. This may cause improper band selection. For example, if there is a need to find a relation between two coefficients, the difference will be evaluated initially. If the difference is high, then the correlation is said to be low. But, if the two coefficients have almost similar values, they their amplitude difference can’t explore that they are correlated to each other or not. If the difference is evaluated between the energies of that coefficients, they it becomes clear that they are correlated or not. This
Evaluation can be done through power spectral density evaluation. Further details about the PSD based sub band selection for medical image coding can be explained in the next section.

4. Spectral Selective Coding

This section illustrates the complete details about the proposed spectral selective coding. In the medical images, every pixel preserves important information which is most important for diagnosis. So, a compression need to apply on the medical where there is less prior information. To achieve this, the energy densities of the wavelet coefficients are evaluated and applied the compression over those coefficients. Only the energy relevant information won’t gives the better visualisation quality. Thus, the obtained image should have degraded PSNR. To achieve efficient coding efficiency, this work decomposes the image through multiwavelet coding. According to the discussion in previous section, the multiwavelet transform decomposes the image in multi directions. i.e., instead of decomposing the LL band alone, the remaining bands such as LH, HL and HH are also processed for further decomposition. This decomposition was applied for \( n \) levels and then the obtained bands will be directly proportional to the number of levels. Further, the bands are selected those having minimum correlation. Here, the correlation is carried out with respect to the amplitudes of the wavelet coefficients. Due to the correlation evaluation in through amplitudes, the bands which are correlated stronger and the bands correlated weaker are not found efficiently. If the correlation is carried out with respect to the power spectral densities of coefficients then, there will be huge difference between the bands it string correlation and the bands with weaker correlation. To achieve this objective, in this approach a spectral selection coding approach is proposed by considering the spectral features of wavelet coefficients during the band selection. Here, the spectral feature correlation is evaluated between the coefficients of bands thus it can be called as spectral coefficients selection. Thus, the redundant information will be reduced further and more efficiently. AS the redundant information is very less, the compression efficiency should be more. The block diagram of the proposed approach is shown in Figure 2.

For the coefficients selection of the selected spectrum, a coefficient selection algorithm is proposed. The developed approach is termed as “Spectral selective coding” (SSC). The process of selective coding is as outlined; for the selected Normalized band ‘BN’ obtained from the decomposition approach, a decision of coefficient selection is made based on spectral magnitude. This approach of selection of coefficients results in coefficients selection, at lower frequency level without effecting higher resolutions coefficients. To compute the spectral magnitude of the band coefficient a power spectral densities (PSD) is computed. The power variations of the signal \( x(t) \) over various frequencies is called as the power spectral density. PSD for the given matrix ‘\( x \)’ varying with ‘t’ is defined as,

\[
P = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} |B(t)|^2 \, dt
\]

Where \( B(t) \) is the band obtained through the multiwavelet decomposition and \( P \) is the power spectral density over a time period \( T \). Taking the selected band ‘\( B_{ni} \)’ as reference, a PSD for each coefficient, ‘\( PB \)’, is computed. The PSD coefficients for the normalized band matrix of dimension \( m \times n \) is defined by,

\[
P_{B_{ni}} = \text{PSD} \left( B_{ni} \right), \text{ for } i = 1 \text{ to } m \text{ and } j = 1 \text{ to } n
\]

The PSD per coefficient is defined as,

\[
P_{PB_{ij}} = \lim_{T \to \infty} \frac{1}{2T} \int_{-T}^{T} B_{Ni,j} \, dt
\]

Where, \( i,j \) are the corresponding row and column, which are read over a time period of ‘\( t \)’. ‘\( t \)’ is the time taken to read the whole set of ‘\( B_{ni} \)’ matrix.
For the obtained power spectral densities of all bands, a correlation factor is measured successively. The correlation is measured for all bands with respect to all bands, i.e., intra bands and inter bands (multi wavelet bands from LL band and the remaining LH, HL and HH bands). The sub bands which having less correlation is selected for further encoding. The bands which have minimum correlation can reduce the redundant information more precisely and also ensures less computational complexity. The band selection procedure based on the correlation is evaluated in the following step by step procedure.

Step 1: Perform Multiwavelet decomposition on the original image, the obtained sub bands can be represented as

\[ B_{LL}^n, B_{LH}^n, B_{HL}^n \text{ and } B_{HH}^n. \]

Step 2: Measure the power spectral densities of all bands through the equation (3).

Step 3: Evaluate correlation between all bands obtained as

For \( k = \{ LL, LH, HL, HH \} \) // types of bands
For \( b = 1 : N \) // number of band for each type
For \( i = 1 : m \)
For \( j = 1 : n \)
\[
\text{cor}_k^b(i, j) = \text{correlation} \left( B_k^b(i, j), B_{k-1}^b(i, j) \right)
\]
End
End
End
End

\[ \left[ mc, b \right] = \min(\text{cor}) \]

Here, the parameter \( \text{cor}_k^b(i, j) \) represents the correlation between the band \( b \) obtained by further decomposing \( k \) type band. \( mc \) is the minimum correlation and \( b \) is the bands having minimum correlation.

Step 4: Like this the correlation is evaluated for all bands and forms the obtained values, the bands with minimum correlation was selected.

Further, the selected bands were processed for further encoding through hierarchical image coding.

For the compression of coefficients then a hierarchical coding is used. The hierarchical algorithm initially divides the entire image into three lists namely, List of Insignificant Pixels (LIP), List of Significant Pixels (LSP) and List of Insignificant Sets (LIS). Then it will encode the entire pixels in the following manner. Every entry of the pixel is identified through its coordinates \( (n_1, n_2) \). In LIS, the entries are sets \( I(n_1, n_2) \) or \( D(n_1, n_2) \), whereas in LSP and LIP, the entries are pixels. In the starting, the maximum magnitude of the coefficients will decide the number of refinement passes which are required to refine the coefficients. At starting, entire coefficients are treated as insignificant. The initialization is followed by three passes: Sorting pass, refinement pass and the quantization step update pass. This process is repeated until the bits with least significance are acquired. In the sorting pass, the sorting of LIPs obtained from earlier stage are sorted to found further which are significant. If the pixel is observed to be a significant, immediately it was moved into LSP. This entire process is repeated for all the sets in the LIS to found the significant sets. Then the obtained significant set is processed to sorting pass to find the significant and insignificant pixels.

The single pixels are added to LIP or to the LSP and the sets with one element are added to LIS. The LSP coefficients are encoded for nthmost significant bit in the magnitude refinement pass. It is observed that, due to compression coefficients into a low spectral magnitude the perceptual quality of the compression image is maintained. The evaluation of this proposed approach is as presented below.

5. Experimental Results

For the evaluation of the suggested approach, various medical sample data are taken. The images are considered with different pixel resolutions and medical cases. In the approach for data compression, the given sample is processed for compression, here, the sample is processed for spectral decomposition, using multi wavelet transformation and a selection criterion based on spectral energy is carried out. The suggested approach of band selection via correlative approach as outlined in 1. Towards an improvement in the compression accuracy, and to minimize the overhead of image compression coefficient, the selected bands are processed in energy domain, where an energy correlation is developed to achieve the coefficient selection for processing. The approach of coefficient selection over the image coefficient result in lower compressing dimension resulting in minimization of processing overhead. The proposed approach is developed for different test sample, and the obtained results are as illustrated.

Figure 3 shows the original sample taken for processing. This original sample is compressed through the both proposed and conventional approaches. The original
sample taken for testing is a uniform sample with uniform size of 256X256.

Figure 4 shows the obtained multiwavelet bands after decomposing the test sample through Multiwavelet (MWVLT) decomposition. In this MWVLT, both the high frequency and low frequency bands are processed for further decomposition. Every band is decomposed into further four bands and the obtained bands for three level decomposition are represented in the figure 4.

After obtaining multiwavelet bands, they are processed for band selection procedure. This band selection is carried out based on the correlation of sub bands. The bands are selected those have minimum correlation. This reduces the redundant information more precisely. Figure 5 shows the selected bands with minimum correlation.

Figure 6 shows the power spectral densities of selected bands to further reduce the redundant information. Since power spectral density give sore prior information, the correlation based on the spectral densities will give more accurate results. This correlation is carried out for the spectral densities of selected bands. Such that the redundant information will be reduced further.

Figure 7 shows the correlated values of the selected bands. The peaks represent the maximum correlated coefficients and the troughs represent the minimum correlated coefficients.

Figures 8-10 represents the recovered test sample through the conventional MWVLT-SPIHT, Band correlative selection and the proposed spectral density correlative approach. From the above figures, it can be observed that the proposed approach obtained more efficient recovered sample compared with conventional approaches.
Further, the performance of the proposed approach was evaluated through the performance metrics such as processing overhead, time taken for encoding, time taken for decoding, mean square error (MSE) and the peak signal to noise ratio (PSNR).

The processing overhead for the developed approach for various observations is shown in the Figure 11. The processing overhead measures the amount of extra burden is occurred during the process of test sample. From Figure 11, it can observe that the proposed spectral correlative image compression having less processing overhead compared with band correlative image compression and the conventional MWVLT-SPIHT.
Energy Interpolated Mapping for Image Compression with Hierarchical Coding

Figure 13. Computation Time for Decoding.

The MSE for the developed method at different level of noise variance is shown in Figure 14. The MSE value is observed to be minimum for the proposed spectral correlative image coding. The approach shows a lower MSE due to the spectral selective nature of coefficient selection. Due to minimal spectral correlative coefficient selection, the MSE of recovered sample is observed to be lower. Wherein this value is higher in the case of MWVLT coding and band correlative coding.

Figure 14. MSE over bit per pixel.

The PSNR measures the qualitative performance of proposed approach. If the PSNR is high, then the proposed approach is said to be achieved better performance. Figure 15 shows the PSNR details of the proposed approach for varying noise variance. From figure.15, it can be observed that, even with the increment in the noise variance, the proposed approach given an optimal PSNR compared with conventional approaches.

Figure 15. PSNR for variant bit per pixel.

Similarly, various samples were processed for testing and the recovered samples are represented in the Table 1. The obtained Processing overhead, computation time, MSE and PSNR are represented in Table 2-5 respectively.

Table 1. Observation for considered test samples

| Original Test Sample | Recovered Sample |
|----------------------|------------------|
|                      | MWVLT-SPIHT       | Band Correlative | Spectral Correlative |
| Original image       | img recovered    | img recovered    | img recovered        |
|                      | img recovered    | img recovered    | img recovered        |
|                      | img recovered    | img recovered    | img recovered        |

The performance evaluation carried out for the test sample represented in Table 1 is represented in Table 2 to Table 4. Table 2 describes the processing overhead details, Table 3 describes the computation time details, Table 4 describes the MSE And Table 5 gives the PSNR details.
Table 2. Overhead observation for the developed approaches

| Test Sample | Processing Overhead | MWVLT-SPIHT | Band Correlative | Spectral Correlative |
|-------------|---------------------|-------------|------------------|----------------------|
|             |                     | 1.6558      | 1.6017           | 1.5823               |
|             |                     | 1.4996      | 1.4230           | 1.3996               |
|             |                     | 1.5132      | 1.4730           | 1.4120               |
|             |                     | 1.4555      | 1.4012           | 1.3866               |

Table 3. Time performance for developed approaches

| Test Sample | Computation Time (Sec) | MWVLT-SPIHT | Band Correlative | Spectral Correlative |
|-------------|------------------------|-------------|------------------|----------------------|
|             |                        | 3.4557      | 2.2230           | 2.8412               |
|             |                        | 2.9567      | 2.7128           | 2.1105               |
|             |                        | 3.9856      | 3.4523           | 2.8824               |
|             |                        | 3.1210      | 2.8883           | 2.5412               |

Table 4. MSE for test samples

| Test Sample | MSE | MWVLT-SPIHT | Band Correlative | Spectral Correlative |
|-------------|-----|-------------|------------------|----------------------|
|             |     | 0.5920      | 0.3610           | 0.1901               |
|             |     | 0.9933      | 0.6331           | 0.4952               |
|             |     | 0.8755      | 0.4222           | 0.2310               |
|             |     | 0.4842      | 0.1507           | 0.1108               |

Table 5. PSNR observation for the developed approaches

| Test Sample | PSNR (dB) | MWVLT-SPIHT | Band Correlative | Spectral Correlative |
|-------------|-----------|-------------|------------------|----------------------|
|             |           | 56.3636     | 57.0358          | 58.2257              |
|             |           | 54.5584     | 55.2231          | 56.0218              |
|             |           | 53.2127     | 54.9871          | 55.9698              |
|             |           | 54.1296     | 55.6552          | 57.2294              |

6. Conclusion

In this paper, a new spectral coding approach is proposed to perform the image compression through hierarchical coding. In this, the image was processed to multiwavelet decomposition followed by spectral feature based band selection. Further the obtained coefficients are processed for encoding through hierarchical coding. Here, the most popular SPIHT was used for encoding. The compression efficiency will be more if the redundant information is less. So, for any image compression there is a need to reduce the redundant information much more. In this proposed approach, due to the coefficients selection through the spectral features, the redundant information is reduced more efficiently.In the approach of spectral coding selection of coefficient selection approach results in higher estimation and accurate estimation of coefficient based on spectral selective coding. The approach of spectral selective coding is defined by the Power spectral density of the obtained spectral bands. The selection criterion is developed based on the energy density concentrations at the pixel level. The proposed selection approach of these coefficient results in effective compression in medical image oriented applications. An improvement in PSNR is observed from conventional approach in proposed approach due to the process of spectral selection in comparison to this conventional based compression approach.
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