Panamerican Mathematical Journal
ISSN: 1064-9735
Vol 35 No. 2s (2025)

An Efficient Medical Image Compression using Modified Set Partitioning in Hierarchical Trees (MSPIHT)

Julian L. Webber[1], Dr. K. G. K. Patnaik[2], Ms. G. Sowmya[3], Abolfazl Mehbodniya[4], Dr. B P Santosh Kumar[5], Sara Samani[6]

[1]Associate Professor, Department of Electronics and Communication Engineering , Kuwait College of Science and Technology (KCST), Doha Area, 7th Ring Road, Kuwait. Email: j.webber@kcst.edu.kw

[2]Associate Professor, MBA, Vignan's institute of information technology (A), Duvvada, Vishakapatnam, Andhra Pradesh, 530040, India. kgkpatnaik@gmail.com

[3]Department of CSE-AI&ML, MLR Institute of Technology, Hyderabad, Telangana, India. Email: sowmya.g@mlrinstitutions.ac.in

[4]Professor , Department of Electronics and Communication Engineering, Kuwait College of Science and Technology (KCST), Doha Area, 7th Ring Road, Kuwait. Email: a.niya@kcst.edu.kw

[5]Associate Professor, Department of ECE, YSR Engineering College Of YVU, Proddatur, email: santoshyvuce@gmail.com

[6]Department of Cardiac Surgery, Chest Disease Hospital, Kuwait, sara.Email: samani@live.com

Article History:

Received: *04-09-2024*

Revised: *23-10-2024*

Accepted: *03-11-2024*

Abstract:

Set Partitioning in Hierarchical Trees (SPIHT) is an effective image compression algorithm. SPIHT is a unique approach which transmits the values of the pixels indirectly to the coordinates. The packet coders in the images present a universal transform the framework in a constriction of the filter bank schema which is attained by the Space Frequency Quantization (SFQ) and the effective compression is achieved by the Huffman coding. The proposed scheme permits transformation in the joints and alterations in the discrete magnitude of the input image. Hence, coding performance is enhanced and the image is compressed without compromising the excellence of the image. MSPIHT is an enhanced algorithm that fits the requirement of medical image compression for storage and transmission of medical data. MSPIHT improves on the standard SPIHT in the encoding operation of wavelet coefficients to provide high quality images at low bit rates important in medical applications where accuracy is paramount. The modification is aimed at changing the set partitioning strategy by minimizing memory consumption rates, thus improving the compression ratio and speed. It also may be used at telemedicine where high image compression rate is required for the quick and efficient image transfer for diagnostics and consultations. Experimental results shows that the image compression scheme is improved with the SPIHT-SFQ based Huffman Coding scheme and it outperforms the current image compression algorithms.

Keywords: Image compression, spatial tree, subband, quantization, wavelet.

INTRODUCTION

The acceptable rate of decompressed image visual quality is preserved by the representation of smaller amount of bits and the intent behind the compression algorithm is to identify the redundancy in the image. Effective representation and the analysation of data are achieved by the wavelets and the establishment of wavelet algorithm is based on the digital signal processing and mathematics [1]. Image compression is one of the prominent applications of wavelets in digital signal processing. Discrete Cosine Transformation (DCT) is a traditional image compression approach and the wavelet based schemes were achieved best results over DCT [3]. The values of the pixels that are resided in the images are not directly transmitted to the content sets which are one of the unique features of SPIHT [4,5,6]. Decisions are made at the generation of the trees that describes the schema of the image. The value of the pixel is made and the outcomes are attained by the decisions at the tree. The key benefit to the decoder scheme in the SPIHT can have an identical algorithm that has the ability to spot every decision and generates identical sets along with the encoder scheme. In this encoder scheme Huffman coding is used to record the bits with the specified rate and the remaining bits directed to the output. Huffman coding saves the bit values during the transmission of image data.

In addition, the strategies of vector or scalar quantization are general subband coding and the representations of hierarchical images are attained with the enhanced quantization schemes [7]. The zero tree quantization is one of the example of frequency and spatial characteristics of wavelet coefficients [8]. A SFQ is designed through zero tree and scalar quantization schemes which lie in the framework of wavelet. A rate-distortion based optimization of the two quantization modes in SFQ offers a best performance. The SFQ scheme may be viewed as a rate-distortion optimized variant of Shapiro’s EZW coder [6]. SFQ scheme in an adaptive transform coding framework by extending the SFQ paradigm from wavelet transform to the signal-dependent wavelet packet transform.

The wavelet representation offers an efficient space-frequency characterization for a broad class of natural images, it remains a “fixed” decomposition that fails to fully exploit space-frequency distribution attributes that are specific for each individual image. Wavelet packets, or arbitrary subband decomposition trees, represent an elegant generalization of the wavelet decomposition [9]. Decomposition of trees can be thought of as adaptive wavelet transforms, capable of providing arbitrary frequency resolution. Combined with their efficient implementation architecture using filter bank tree structures, the wavelet packet framework has opened a new avenue of wavelet packet image coding. Wavelet packet SFQ coder undertakes the joint optimization of the wavelet packet transform and the powerful SFQ scheme. Experimental results confirm the high performances of new coder algorithm.

Technological advancements in the field of medical imaging has hence had a positive impact on health delivery whereby Clinicians are in a position to see the ailments they are diagnosing. Nevertheless, high quality medical images like MRI, CT or ultrasound scans consume massive storage; for transmission, telemedicine, remote diagnosis and EHR indeed present specific challenges. It is of paramount importance, therefore, to compress such images in an efficient manner for the purposes of both storage costs and transmission times without prejudice to diagnostic quality.

The MSPIHT is an improved technique for the above mentioned challenges using the classical algorithm called Set Partitioning in Hierarchical Trees (SPIHT). SPIHT is one of the most used wavelet based image compression technique which uses progressive transmission and show very high compression ratio suitable for natural images. Nonetheless, its use in medical images that must retain the necessary level of detail for diagnostic purposes has not been optimized so far. As a result of modifications made on the set partitioning and encoding process, MSPIHT is enhanced from SPIHT. This modification makes it possible for MSPIHT to give attention to the regions of the medical images that are of great importance and at the same time make the unnecessary areas to be compressed in high quality.

As a result, MSPIHT is able to strike a balance between compression ratio and quality thereby being appropriate in both storage and bandwidth limited scenarios. Of course, the efficiency of using MSPIHT is significant for the telemedicine and other cloud-based medical applications, where fast and secure workflow for the exchange of the medical information is crucial for making the correct decisions. By using the MSPIHT, the healthcare centers can enhance the features of storing and transmitting data while achieving high picture quality needed for diagnosis. Also, the computational complexity of the proposed algorithm is optimal for implementation on mobile and edge devices, increasing its utility even further. Altogether, MSPIHT is a great development in medical image compression, which allows finding a practical solution for the problems of Health care data management systems.

I. RELATED WORK

Kim, H., No, A., & Lee, H. J. [10] had developed a novel one-dimensional Discrete Wavelet Transformation (DWT) and SPIHT algorithm. The proposed algorithm attained effective compression and minimized computational complexity. Complexity in the block was identified using the DWT algorithm and the simple blocks in the media was compressed in an effective way.

Fry, T. W., & Hauck, S. A. [11] introduced a reconfigurable logic in SPIHT. The proposed approach is designed based on the fixed order. Architecture and folded design of DWT was designed on an Annapolis Microsystems. The system accomplished a 450/spl times/ speedup versus a microprocessor solution, with less than a 0.2-db loss in peak signal-to-noise ratio over traditional SPIHT.

Xiong, Z., et al [12] incorporated scalar quantization and the joint applications were optimized. The author had addressed the issues in the standard scalar and spatial quantization techniques that were raised in the image coder approaches. The proposed scheme had reduced the optimality issue in image compression.

Velisavljevic, V., et al [13] projected a method for the creation of significantly sampled perfect reconstruction transforms with directional vanishing moments the entailed in the relevant basis functions along varied directions, called directionless. The complexity in the process of image compression is minimized in the projected approach when tested with the traditional SFQ algorithm.

Saravanan, C., & Surender, M. [14] presented a lossless compression approach that is developed with Huffman coding. The compression of image is attained by Huffman coding in the initial stage. In the subsequent phase concatenation is processed with Lempel Ziv coding method. Compression and decompression of images were achieved with better results in the proposed scheme.

Gaudio et al. (2023) propose DeepFixCX, a privacy-preserving and explainable framework for compressing medical images. In order to meet the need for both model interpretability and patient information confidentiality, DeepFixCX reduces the image size by masking selective spatial and edge details to anonymise patients while retaining the pictures' feasibility. This lightweight approach works at high throughputs, with up to 1700 images per second; it also works well with low-memory MLP classifiers to provide accurate diagnostics in medical imaging. The framework is assessed on datasets for Glaucoma and Cervix Type identification, enhancing DNN performance by 0.02 AUC ROC, making for considerable innovation in safe, effective medical imaging.

In this research, Xue et al. (2023) introduce a new hybrid steganographic, WT and advanced compression model for lossless medical image compression in order to optimize storage space and data security. With KT for secure data placement and DWT for image safeguarding, the model has high compression rates that maintain the image quality and scalability for large medical databases. Achieving compression ratios of 7.8%-8.6%, this approach enhances data storage and data retrieval by up to 60% more efficient compared to previous methodologies, while alleviating significant privacy and storage issues in health care.

Monika and Dhanalakshmi (2023) proposed a medical image compression method based on the ABCS with CMT-ABCS for telemedicine applications. It has been used to select the sample in image regions that provides higher compression ratios and better performance measures than other Compressed Sensing (CS) techniques. This method brings a huge enhancement to metrics; the PSNR raises from 5 to 10 dB; The SSIM raising from 0.1 to 0.2; However, it keeps a clear diagnostic quality and only needs 10% sampling rate. CMT-ABCS adopted achieves significant reduction in size of large medical image datasets for transmission and storage in telemedicine for diagnosing and monitoring patients remotely.

In their work of 2024, Dodda et al. present Artificial Intelligence approaches for improving image exchange in medical imaging networks for the better real-time diagnostic capabilities. They propose an approach that combines the CNN, GAN, and image filters that enhance data transmission, diagnostic precision, and latency in MRI, CT & Ultrasound technologies. There results demonstrate better results than typical compression approaches, accurately labeling anatomic structures and detecting pathologies. This paper presents a system that allows for the transfer of images and facilitate image analysis for telemedicine applications and for the enhancement of healthcare service delivery and patient care. This work demonstrates the raw power of AI to revolutionalize compute-intensive medical imaging applications.

II. PROPOSED IMAGE COMPRESSION FRAMEWORK – SPIHT-SFQ BASED HUFFMAN CODING

The proposed Huffman coding framework uses SPIHT-SFQ which incorporates wavelet transforms, spatial tree structures and quantization to achieve image compression with minimization of image quality as much as possible. This approach is particularly relevant to medical images since maximizing retention of image features is essential. It employs a spatial tree concept based on wavelet coefficients to group image data into different bands of frequency and hence show spatial interactions of the image pixels. The structured organization of the components of an image ensures that only one pass through the wavelet-transformed image is necessary to decide which components offer relevant information. This framework is centered on the SPIHT (Set Partitioning in Hierarchical Trees) algorithm, which first forms a subband tree.

In this tree each level is corresponding to different frequency bands of the image, and every coefficient is connected to child coefficients. This arrangement where the HH, HL and LH sub-bands represent high frequency components such as edges and textures and the LL sub-band retains lower frequency, broader information regarding the image. An enhancement of the basic SPIHT algorithm called MSPIHT sorts image data into three ordered lists that differentiate image pixels according to their importance. This approach enables the center of mass computation on such data, thus enabling the compression of the image without loss of crucial information.

Compression itself is effected through three phases: sorting, enhancement, and quantization. In the sorting phase, the algorithm chooses which of the coefficients are important in the picture, getting the features which are important, while the other details which are not as important are discarded here. During enhancement phase, these selected coefficients are further improved, making image clearer and maintaining the detail. Lastly, the quantization phase entails a process of thresholding that eliminate much of the redundancy inherent in the compression process thus require minimal storage space to store the compressed image. Altogether, the components allow a high efficiency and low loss compression that is effective to medical image applications that need to store and share diagnostic images.

The concept of the Image Compression Framework – SPIHT-SFQ based Huffman Coding creates the spatial tree structure from the wavelets that transforms coefficient packet of wavelets. The spatial tree structure spots varied frequency bands among the relationship of spatial relationship. The design of the quantizer and joint transform permits the exploration is a single scan through wavelet.

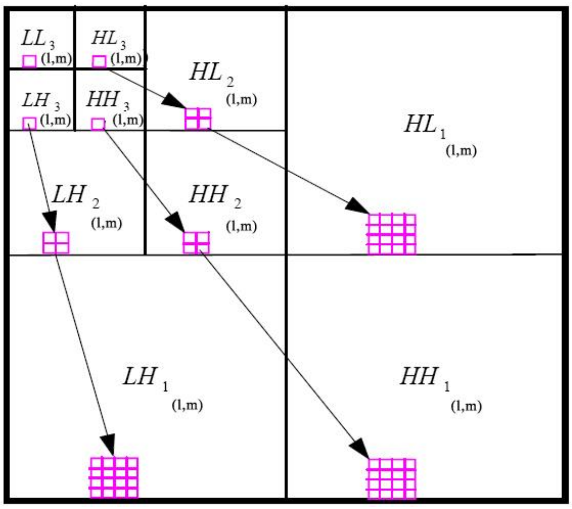


Figure 1. Structure of Wavelet Tree SPIHT Algorithm

Initially, entire subband tree is constructed and the optimal solution is identified in the pruned tree. Significance in the wavelet is indicated by equation1. In equation 1, l and m denotes the wavelet coordinate position.

$$W_n(X) = \begin{cases} 1, & maxim\left\{\left|co_{l,m}\right|\right\} \geq 2^n, where\ l,m \in X \\ 0, & others \end{cases} \qquad \text{----------------- (1)}$$

The data about the image and the coefficients of the image distribution via wavelet is generated as a tree and the tree structure is represented in 4 levels. Every coefficient holds four children and the subband with best subbands are HH1,HL1,LH1. The subband LL holds least coefficient which is represented through figure 1. In the figure 1, l and m specifies the row and column indices of coordinate set. H is the root of the orientation of the spatial tree and $CO(l,m)$ are the set of offspring for the coefficient (l,m).

$O(l, m) =\{(2l, 2m), (2l, 2m + 1),(2l + 1, 2m), (2l + 1, 2m + 1)\}$, except (l, m) is in LL, When (l,m) is in LL is the subband and O(l, m) is stated as: O(l, m) = {(l, m + width_LL), (l + height_LL, m), (l + height_LL, m + width_LL)},

where, width_LL and height_LL is the width and height of the LL subband, respectively.

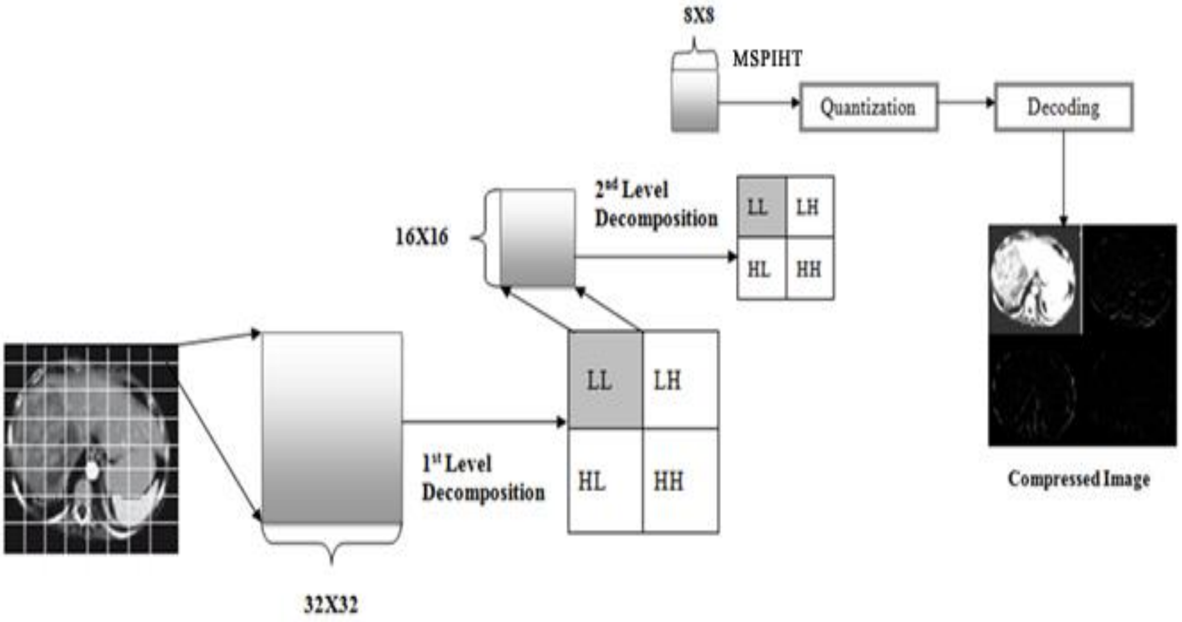


Figure 2. Image Compression using MSPIHT Algorithm

D(l, m) is the set of all descendants of the coefficient (l,m), L(l,m):D(l,m)-O(l,m). A function $W_n(X)$ decides the set of coordinates with the threshold of 2_n is stated in equation 1.

In the MSPIHT algorithm, significant information generated during the partitioning of set is stored in the ordered list. List of insignificant set (LSI), list of insignificant pixels (LPI) and list of significant pixels (LPS) are the three ordered list used for storing the values. The pixels in the list denote coefficient factors of the wavelets in the image. The process is given in Algorithm 1.

Algorithm 1. Stepwise Procedure for MSPIHT

Initialization

In the initialization process the input image is loaded for the compression and all the three ordered lists are initialized with needed values.

$n = \lfloor \log_2 \max\{|co_{l,m}|\} \rfloor$

Set LPS=∅

Set LPI = (l,m) ∈ H

```
Set LSI = (l,m) $\in$ H, where D(l,m) $\neq \emptyset$
```

Arranging the pass

In the sorting process, all the insignificant pixels are checked with the coefficient sets and the coefficient sets are checked. The significant values are appended into the list.

```
for each(l, m) $\in$ LPI do:
output $W_n(l,m)$
if $W_n(l,m) = 1$ then move (l, m) to LPS and output sign CO(l,m)
end for
for each (l, m) $\in$ LSI do:
if (l, m) is equal D(l, m) then
output $W_n$ (D(l, m))
if $W_n$ (D(l; m)) = 1 then
  for each (k, l) $\in$ O(l, m)
  output $W_n(k, l)$
  if $W_n$ (k, l) = 1 then append (k, l) to LPS, output sign(ck,l),and ck,l = ck,l- 2n sign(ck,l)
else append (k; l) to LPI
move (l, m) to the end of LIS as type B
if (l, m) is type B then
  output Sn(L(l, m))
if Sn(L(l, m)) = 1 then
  append each (k, l) $\in$ O(l, m) to the end of LSI
  remove (l, m)from LPS
end for
```

Enhancing the pass

The process of enrichment of the pixels is initiated at the enhancement phase and the every coordinate set in the significant pixels are moved to the enhancement phase after the sorting process.

```
for each (l,m) in LPS, except those included in the last sorting pass
Output the $n$-th phase of $CO|C_{l,m}|$
end for
```

Quantization

In the quantization process, coordinate set remains in the phase is again shifted to the arrangement phase.

```
decrement $n$ by 1
repeats the arranging process
```

III. EXPERIMENTAL EVALUATION

The brain tumor data were obtained from figshare, SARTAJ, and Br35H and contain 7,023 MRI images of human brains. These images are divided into four classes: benign brain tumour including glioma, meningioma, Pituitary tumour and no tumour. The “no tumor” images come from the Br35H dataset, but concerns regarding the glioma class in SARTAJ led to the use of images from figshare for better categorization. In the context of image compression this dataset is an important resource in the development of techniques that can allow for optimal storage and transmission of medical images while not affecting diagnostic quality.

Techniques like wavelet based or deep learning based are employed to keep the essential features of the data intact while compressing the data. The variation in the number and size of images in the available dataset requires resizing as well as the elimination of margins among other processes. This kind of preprocessing is especially important to achieve good compression and high quality of reconstructions especially when using Convolutional Neural Networks (CNNs) or other forms of high level compression. Combining image compression techniques with this dataset enables researchers to investigate real-world image compression that retains image quality for diagnostic uses but with less storage space needed. It is important for healthcare environments where there is need to transfer or archive a huge amount of MRI data.

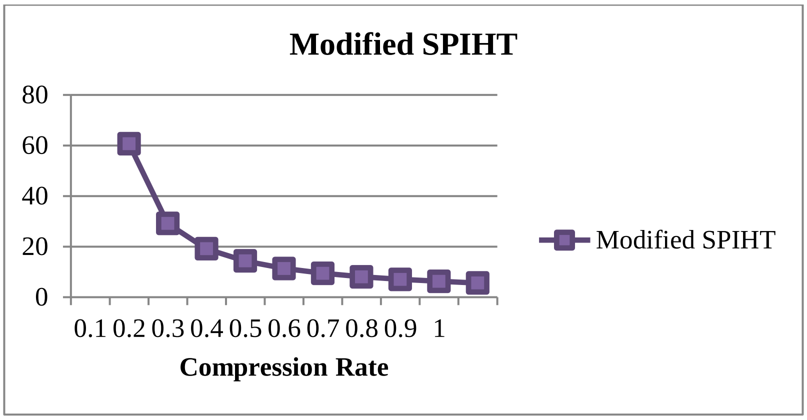


Figure 3. Data Compression Rate

The obtained results are presented in the form of figures and tables which gives a clear understanding of the performance of image compression. In Figure 3, the data compression rate is compared with the key performance indicators to determine the effect of the compression rate on image quality. The higher the level of compression rate the better is the quality of the image that is reflected by the parameters such as the MSE (Mean Squared Error) and PSNR (Peak Signal-to-Noise Ratio).

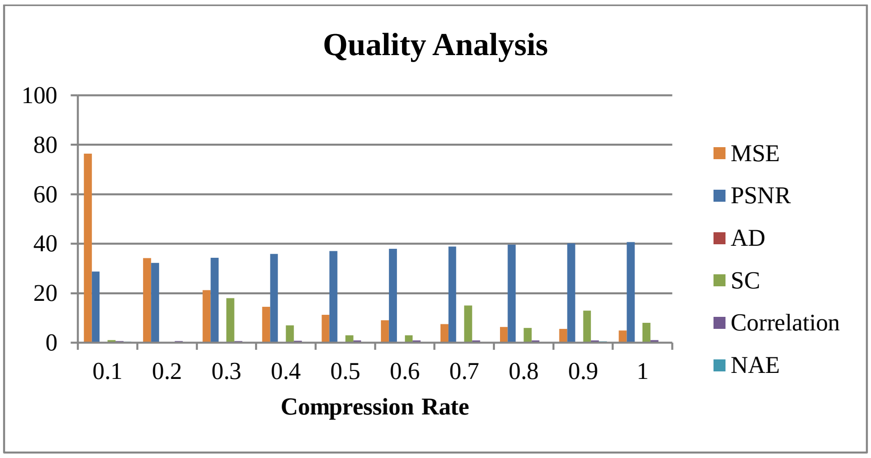


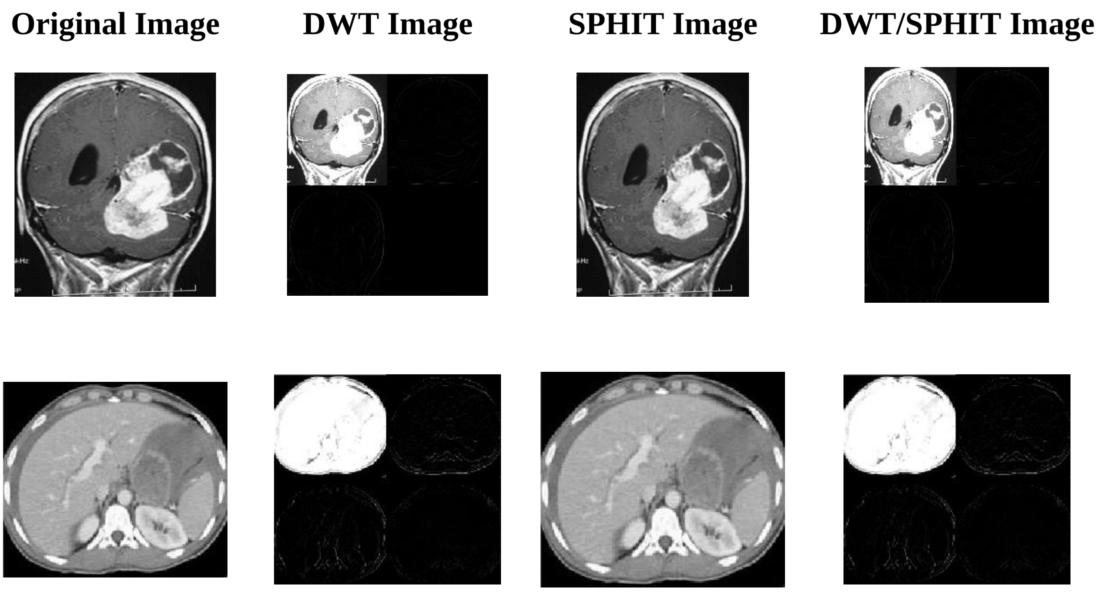
Figure 4. Performance Comparison of Across Diverse Data Compression Rate

Figure 4 analyzes the differences in algorithms' performance depending on the compression rate to show the effect of compression on the image quality and the preservation of critical elements.

Table 1. Performance Comparison of Across Diverse Data Compression Rate

Compression rate	MSE	PSNR	AD	SC	Correlation	NAE
0.1	76.42	28.7	0.0378	1	0.6	0.4
0.2	34.25	32.2	0.0456	0	0.69	0.31
0.3	21.24	34.3	0.0456	18	0.7	0.3
0.4	14.50	35.9	0.0105	7	0.79	0.21
0.5	11.22	37.1	0.0105	3	0.85	0.15
0.6	9.05	38.0	0.0105	3	0.87	0.13
0.7	7.57	38.8	0.0036	15	0.89	0.11
0.8	6.31	39.6	0.0036	6	0.9	0.1
0.9	5.51	40.1	0.0036	13	0.95	0.5
1	4.89	40.7	0.0036	8	0.98	0.2

Table 1 presents detailed numerical analysis of compression rates ranging from 0.1 to 1. This comprises, Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Average Distance (AD), Structural Content (SC), correlation and Normalized Absolute Error (NAE). The table shows that as the compression rate is higher the image quality is better based on the decrease of the MSE and increase of PSNR. For example, when the compression ratio of 1, the obtained image PSNR is 40.7, and the image quality is high, while the MSE is 4.89.



Original Image **DWT Image** **SPHIT Image** **DWT/SPHIT Image**

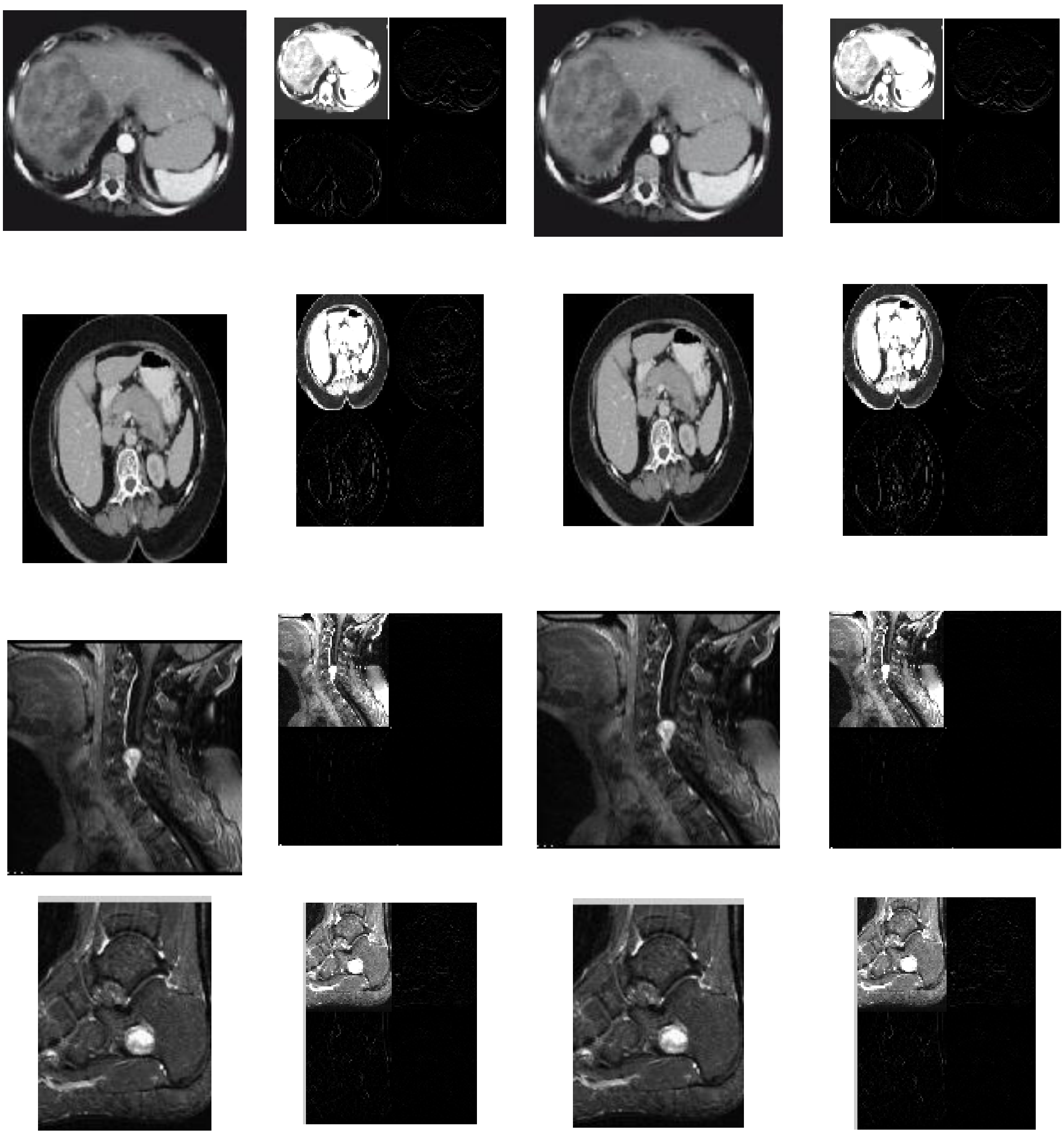


Figure 5. Data Compression Outcome

Figure 5 below displays compressed data results in the form of images; original image is compared with images compressed using DWT, SPHIT and DWT/SPHIT. It emphasizes how the techniques influence the image quality in the view of the observer.

Table 2. Performance Comparison of DWT

IMAGE	PSNR	MSE	ENTROPY	SSIM
IM1	16.44	1.60	3.64	0.07
IM2	14.80	11.37	3.22	0.10
IM3	15.70	2.68	4.10	0.09
IM4	14.20	3.00	2.99	0.12
IM5	16.98	5.05	3.76	0.05
IM6	15.57	6.81	3.89	0.01

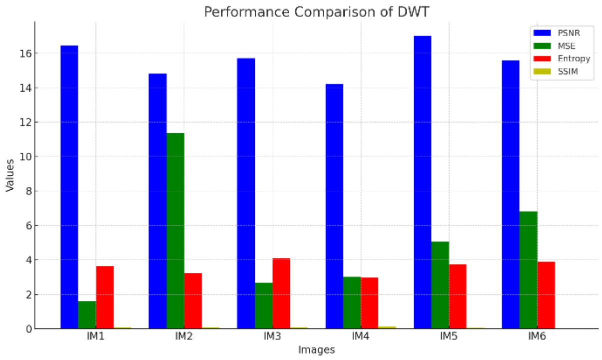


Figure 6. Performance Comparison of DWT

Table 2 speaks about the performance comparison of the proposed DWT compression with the help of parameters like, PSNR, MSE, entropy, and SSIM for various images. The analysis of the results prove that DWT is quite efficient and the achieved PSNR values vary from 14.20 to 16.98 Nevertheless the efficiency of the algorithm is not stable in the same manner as in case with SPIHT. These trends are further highlighted and clearly illustrated in figure 6 where DWT method is plotted against images 1 to 10.

Table 3. Performance Comparison of SPIHT

IMAGE	PSNR	MSE	ENTROPY	SSIM
IM1	54.01	0.22	1.10	0.86
IM2	54.82	0.21	1.02	0.96
IM3	54.70	0.20	1.00	0.88
IM4	54.20	0.23	0.90	0.91
IM5	55.08	0.15	0.00	0.89
IM6	53.97	0.28	0.89	0.91

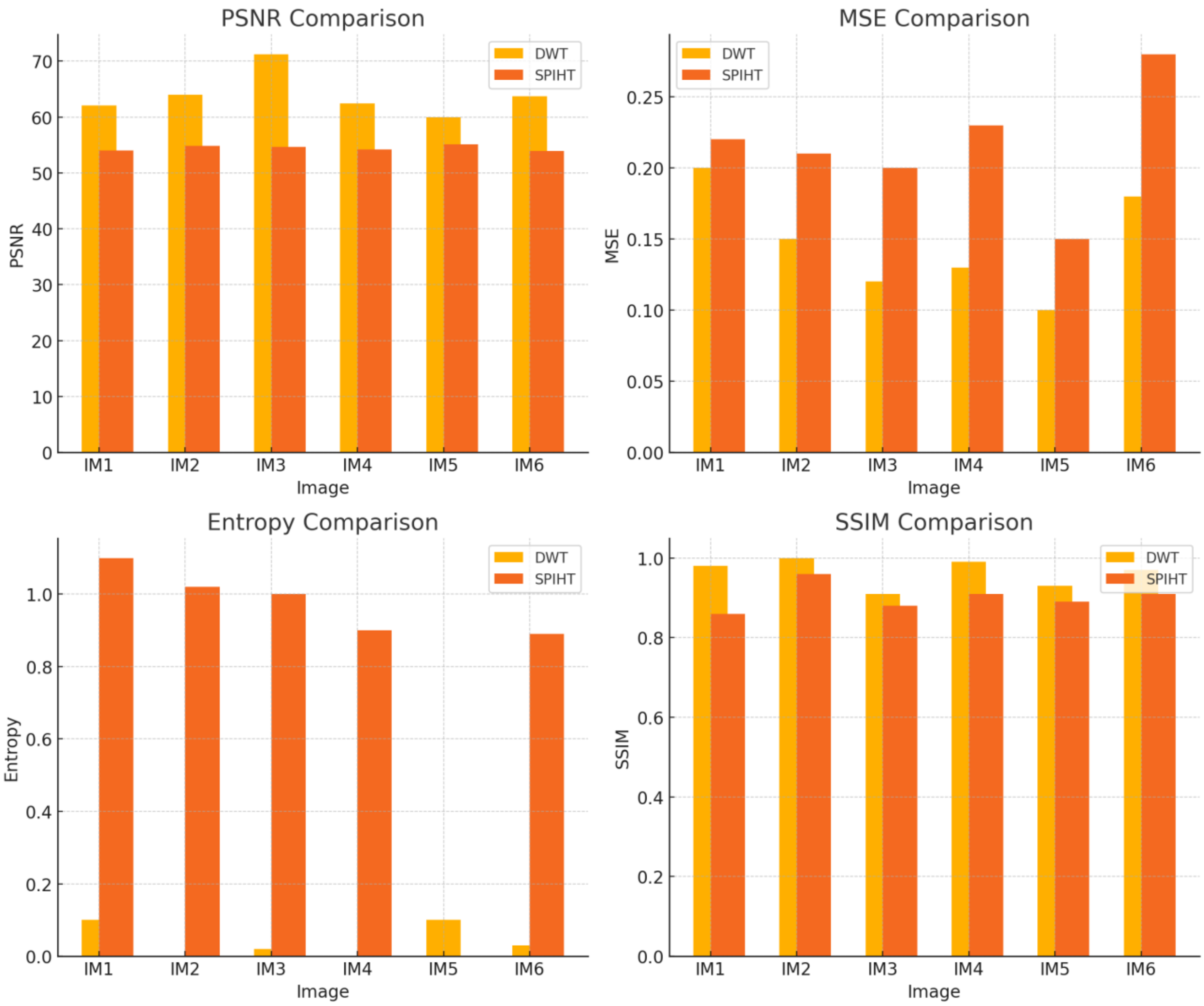


Figure 7. Performance Comparison of SPIHT and DWT/SPIHT

The performance of SPIHT is presented in the Table 3 which also indicates the improvement in image quality the PSNR from 54.01 to 55.08 and the MSE from 0.00194 to 0.00036. Figure 7 shows these improvements of compression performance using SPIHT as follows.

Table 4. Performance Comparison of DWT/SPIHT

IMAGE	PSNR	MSE	ENTROPY	SSIM
IM1	62.11	0.20	0.10	0.98
IM2	64.02	0.15	0.00	1.00
IM3	71.27	0.12	0.02	0.91
IM4	62.40	0.13	0.00	0.99
IM5	59.98	0.10	0.10	0.93
IM6	63.71	0.18	0.03	0.97

Table 4 shows the comparison of the DWT/SPIHT combined method which has yielded the best performance in all the tested image. The obtained PSNR values are in the range of 59.98–71.27, which proves the higher image quality as compared to the results obtained using DWT or SPIHT separately. This is also evident by the observed higher SSIM values where the combined method has comparatively less distortion and distortion of the structure of the original images. Figure 7 provides a clear indication that indeed the use of DWT/SPIHT is appropriate for use in image compression since it has been effective not only in improving the quality of the compressed images but also in increasing the level of efficiency that comes with the whole exercise.

IV. CONCLUSION

In this paper, an effective image compression algorithm is projected with the incorporation of SPIHT. The Space Frequency Quantization (SFQ) is used for the packet coders that alter the framework in a constriction of the filter bank schema is attained and the effective compression is achieved by the Huffman coding. The proposed scheme permits transformation in the joints and alterations in the discrete magnitude of the input image. The performance of the compression is enhanced and the image is compressed without compromising the excellence of the image. Illustration results show that the image compression scheme is improved with the SPIHT-SFQ based Huffman Coding scheme and it outperforms the current image compression algorithms.

REFERENCE

[1] Mallat, S. (1999). *A wavelet tour of signal processing*. Elsevier.

[2] Li, M. L., Qi, H. Y., Nie, F. S., Wen, Z. N., & Kang, B. (2003). Application of embedded zerotree wavelet to the compression of infrared spectra. *Chinese Chemical Letters*, *14*(11), 1193-1195.

[3] Tharini, V. J. (2024). Cross-Entropy Assisted Optimization Technique for High Utility Itemset Mining from the Transactional Database. *Communications on Applied Nonlinear Analysis, 31*(3s), 90-104.

[4] Saraf, P. D., Sisodia, D., Sinhal, A., & Sahu, S. (2012, December). Design and implementation of novel SPIHT algorithm for image compression. In *2012 2nd IEEE International Conference on Parallel, Distributed and Grid Computing* (pp. 430-434). IEEE.

[5] Nair, L. S., & Joshy, L. M. (2015). An improved image steganography method with SPIHT and arithmetic coding. In *Proceedings of the 3rd International Conference on Frontiers of Intelligent Computing: Theory and Applications (FICTA) 2014* (pp. 97-104). Springer, Cham.

[6] Tharini, V. J., & Shivakumar, B. L. (2022). High-utility itemset mining: fundamentals, properties, techniques and research scope. In *Computational intelligence and data sciences* (pp. 195-210). CRC Press.

[7] Kassim, A. A., & Lee, W. S. (2003). Embedded color image coding using SPIHT with partially linked spatial orientation trees. *IEEE Transactions on Circuits and Systems for Video Technology*, *13*(2), 203-206.

[8] Woods, J. W. (Ed.). (2013). *Subband image coding* (Vol. 115). Springer Science & Business Media.

[9] Shapiro, J. M. (1993). Embedded image coding using zerotrees of wavelet coefficients. *IEEE Transactions on signal processing*, *41*(12), 3445-3462.

[10] Kim, H., No, A., & Lee, H. J. (2018). SPIHT algorithm with adaptive selection of compression ratio depending on DWT coefficients. *IEEE Transactions on Multimedia*, *20*(12), 3200-3211.

[11] Fry, T. W., & Hauck, S. A. (2005). SPIHT image compression on FPGAs. *IEEE Transactions on circuits and systems for video technology*, *15*(9), 1138-1147.

[12] Xiong, Z., Ramchandran, K., & Orchard, M. T. (1997). Space-frequency quantization for wavelet image coding. *IEEE Transactions on Image Processing*, *6*(5), 677-693.

[13] Velisavljevic, V., Beferull-Lozano, B., & Vetterli, M. (2007). Space-frequency quantization for image compression with directionlets. *IEEE Transactions on Image Processing*, *16*(7), 1761-1773.

[14] Saravanan, C., & Surender, M. (2013). Enhancing efficiency of huffman coding using Lempel Ziv coding for image compression. *International journal of soft computing and Engineering*, *2*(6), 38-41.

[15] Gaudio, A., Smailagic, A., Faloutsos, C., Mohan, S., Johnson, E., Liu, Y., ... & Campilho, A. (2023). DeepFixCX: Explainable privacy-preserving image compression for medical image analysis. *Wiley interdisciplinary reviews: Data mining and knowledge discovery*, *13*(4), e1495.

[16] Xue, X., Marappan, R., Raju, S. K., Raghavan, R., Rajan, R., Khalaf, O. I., & Abdulsahib, G. M. (2023). Modelling and analysis of hybrid transformation for lossless big medical image compression. *Bioengineering*, *10*(3), 333.

[17] Monika, R., & Dhanalakshmi, S. (2023). An efficient medical image compression technique for telemedicine systems. *Biomedical Signal Processing and Control*, *80*, 104404.

[18] Dodda, S., Chintala, S., Kanungo, S., Adedoja, T., & Sharma, S. (2024). Exploring AI-driven Innovations in Image Communication Systems for Enhanced Medical Imaging Applications. *Journal of Electrical Systems*, *20*(3s), 949-959.