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Hybrid medical image compression using the IKL transform with an efficient encoder

S. Saravanan[a,*], Sujitha Juliet[a]

[a] *Department of Computer Science and Engineering, Karunya Institute of Technology and sciences, India.*

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Abstract

Medical images are generated in a huge number in the research centers and hospitals every day. Working with the medical images and maintain the storage needs an efficient fund and huge storage space. Retaining the quality of the medical image is also very essential. Image compression without losing its quality is the only term to achieve the desired task. Achieving the desired task using the integer Karhunen Loeve transform attains a quality output and also with less storage space. JPEG and JPEG 2000 are also challenging to the integer transform based compression. Resulting the compression quality in terms of peak signal noise ratio, compression ratio is attained. Proposed method of compression is compared with the other efficient algorithms. Thus this proposed method can be used efficiently for the medical image in order to store and retrieve in healthcare industry.

Keywords: Image Compression, IKLT, SPIHT
2010 MSC: Primary 90C33; Secondary 26B25.

1. Introduction

The raise of digital images usage leads to the use of more work over the multimedia computing. Using the raw images for manipulation, storage and transmission of these images has become more expensive, and it also slows the transmission and orders more cost for storage. Due to the enormous use of digital imaging requires holding the huge different set of volumes data as digital images. Hence the role of image compression is required for minimizing the entire data volumes to represent an image. Over medical images, generated through various acquisition devices that produces a large data volume of medical data set. Compressing Medical images is still a challenging task to obtain

*Corresponding author
Email addresses: saranrulz671@gmail.com (S. Saravanan), sujitha.juliet@gmail.com (Sujitha Juliet)

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without quality loss for diagnosis. It requires a low fidelity loss for avoiding the diagnostic errors[1]. And more over the compressed medical image needs to be identical to the one of original image that illustrates that the compression technique should be a lossless one or a high-fidelity method.
Compression over images takes the main role of reducing the redundancy on pixel of an image for storage and transmission in an effective way [2]. Properties which are considered over the compression are Compression ratio, Resolution scalability, Computational time and PSNR that decides the quality of the compressed image. Though enormous number of algorithms has been proposed for the purpose of lossy and lossless compression techniques, finding an efficient algorithm is still a challenge. Important aspect required especially for medical images are high directionality, general scaling, multiresolution and decorrelating features. For achieving higher performance metrics and producing a visually lossless compression techniques remains a challenging task.
This paper presents an efficient framework for compressing a medical image in detail as the following sections. A detailed survey on the existing compression algorithms are discussed in section 2. Basic concepts of general KLT, IKLT and SPIHT encoder algorithms are dealt in section 3. Proposed compression scheme is introduced in section 4. Performance evaluation methodologies are analyzed in section 5 and conclusions are specified in section 6.

2. Literature Survey

Over the huge demand of Medical data used for diagnosis [3], the demand on medical image compression algorithms also raised to a new hike of demand. And it has been categorized into lossless and lossy compression. In order to achieve a compression over a medical image, consideration has led towards the lossless based method of compression. Huffman coding[4], Arithmetic coding [5], Run length encoding [6], Predictive coding [4], LZW coding[6] are famous methods generally used to achieve the lossless image compression methods, where Huffman coding is an entropy based coding which is commonly used for other algorithms as a hybrid compression models. Arithmetic coding works on the probabilistic occurrence of symbols and represents a message with 0 and 1 intervals. Run Length Encoding [6] works on the repeated values and count of repeated values method whereas predictive coding depends on the prediction error based on the finding errors over the neighboring pixels. LZW[6] is a dictionary coding and its very much appropriate for text encoding methods. There are further more hybrid compression models that emerges from the combination of two or more algorithms which also result in achieving the lossless compression. Wavelet transform and vector quantization hybrid model [7] proposed results in achieving a good compression rate, where it achieved with a help of a codebook generation algorithm. Sparse Fast Fourier based transform method [8] which also achieves a high compression rate and the author proves it by comparing with the other existing combination of compression models. Combination of DCT with DWT [9] proposes the wavelet based decomposition model to achieve a higher PSNR rate and Differential Pulse Code Modulation[10] is also used as a quantizer in order to enable a significant correlation to achieve a lower bit rate. An another LPC-DWT-Huffman [4] method which achieves a lossless result by combining the LPC transform with a wavelet transformation in order to reduce the redundancy and spatial reputation and finally combined with a Huffman coding. Combination of KLT transform with an SVD encoding [11] performs a way higher than the standard algorithms in terms of PSNR.
SVD (Singular value decomposition) [6], moved by its excellent energy compaction with its least square sense. Main drawback of using SVD is that it needs to recalculate for each subsets in an image [6][1]. And the best entropy method SPIHT[12] which is a Set Partitioning In Hierarchical Trees, brings the highlights of achieving a good performance with embedded encoding and low complexity. KLT [13], is a transform depends on the data to be transformed and its matrix consist of eigen

vectors derivative from the covariance matrix of all the data. Using KLT result in actual decorrelate one of the spectral bands with more than 20dB but the drawback is the change is expensive when it considered for calculation. To replace the drawbacks of KLT, Integer based KLT (IKLT)[5] is used in replace of the general KLT as the Invertible IKLT which converts integer to integer for creating a lossless compression. The IKLT is based on matrix [14] and it has been tested with the hyperspectral images with a STW (Spatial-orientation Tree Wavelet) and achieves the better compression ratio. From the survey it's decided to propose a method of having a compression model using integer KLT to obtain an efficient lossless compression technique, which is detailed in the section 4.

3. Proposed Method:

In this proposed method, sample medical images are collected and encoded using the Integer based Karhunen Loeve Transform for obtaining a lossless compressed image transform coefficents. With the usage of SPIHT encoder, the medical images considered for attaining a noise-less output image with a high PSNR value. At the same time, the resultant values are compared with the state-of-the-art existing compression algorithms in order to find the efficiency of the proposed method. Integer KLT is a well-known optimal transform which is an appropriate method for approximating the set of vectors also known as orthonormal linear transformation.

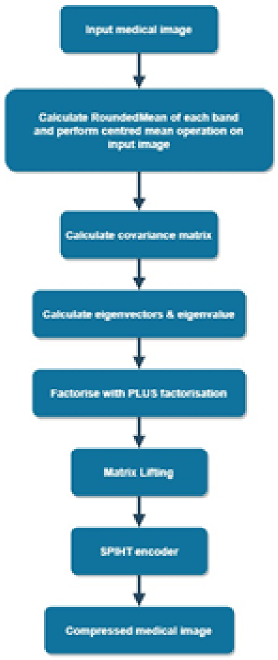


Figure 1: Flowchart of medical image compression using IKLT with SPIHT

3.1. Image selection for Proposed method:

The proposed compression scheme is illustrated as a block diagram in Fig 1. Sample medical images are collected from Scan center for experimentation. Input medical raw DICOM images are taken into the transform for decomposition process which was achieved by Integer based KL Transform.

For achieving a better compression ratio with respect to maintaining the lowest distortion, process of converting from a pixel domain to other domains is mandatory. Decorrelation of pixels, which is more important in transform domain, tends to achieve the higher compression ratio. The transform which completely decorrelate the pixels on the image is said as optimal transform [15]. KLT is a well-known optimal transform which is an appropriate method for approximating the set of vectors also known as orthonormal linear transformation. KLT deals with more on the statistics of the input samples. Though, the output achieved by the KLT is non-reversible as it has a floating-point number and it needs to be rounded off which results in lossy compression. KL transform of the input matrix as represented in [16] as

$$KL\ Transfrom = \left\{ \begin{bmatrix} E_0 & E_1 \\ E_2 & E_3 \end{bmatrix} * \begin{bmatrix} a & b \\ c & d \end{bmatrix} \right\} \tag{3.1}$$

From (3.1) using the matrix multiplication, it can be modified as

$$KLTransform = \begin{bmatrix} (E_0a + E_1c) & (E_0b + E_1d) \\ (E_2a + E_3c) & (E_2b + E_3d) \end{bmatrix} \tag{3.2}$$

$$\text{KL Transform } = \begin{bmatrix} KL_0 & KL_1 \\ KL_2 & KL_3 \end{bmatrix} \tag{3.3}$$

Where $KL_0 = (E_0a + E_1c)$; $KL_1 = (E_0b + E_1d)$; $KL_2 = (E_2a + E_3c)$; and $KL_3 = (E_2b + E_3d)$

3.2. Integer based KLT

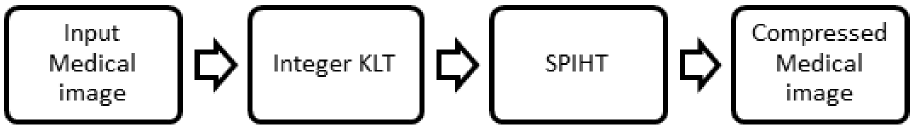


Figure 2: Proposed compression method

The Integer based Karhunen-Loève Transform (Integer KLT) was proposed based on matrix factorization which produces an integer output [17]. Integer KLT has been used to achieve the quality less spectral decorrelation. In [18] Blanes et all presented a multilevel, huddled version of the IKLT algorithm with a degree for lossy-to-lossless coding. The positive side of the Integer KLT will be as high energy compaction, moderate computational complexity and to the most a lossless conversion.[17] a reversible integer based version of transform $\tilde{y} = By$ achieved by lifting process as

$$\widetilde{y_m} = \begin{cases} b_{mm}y_m & + \left[\sum_{n=m+1}^{M} b_{mn}y_n \right]_z, \; m = 1, \ldots, M-1 \\ b_{mm}y_m, & m = M \end{cases} \tag{3.4}$$

Where $[.]_z$ represents rounding the nearest integer. Subsequently the KLT is an orthonormal transform, the factorization is used which approximates the KLT. According to the HAO and SHI' s algorithm [17], factorized matrix A as $A = PLUS$ where P denotes permutation matrix, U states as an upper TERM where L and S as lower unit TERM. For integer to integer of matrix A is represented as

$$\widetilde{A} : Z^N \to Z^N, \tilde{A} = P\tilde{L}\widetilde{U}\tilde{S} \tag{3.5}$$

3.3. SPIHT Encoder

When the decomposition of the input image is obtained using integer-based $KLtransform$, then it is allowed to encode the coefficients in order to achieve the efficient result, considering the space. Many encoding algorithms for compressing the images based on wavelets have been recently developed. Out of the most efficient algorithms that accomplish pixel accuracy and resolution using SPIHT algorithm[12].

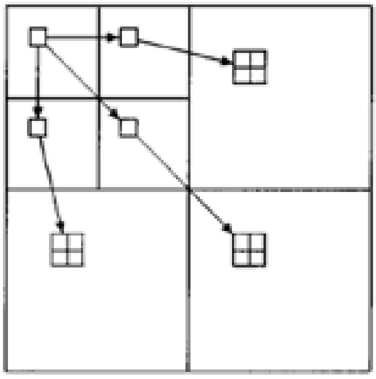


Figure 3: Tree Structure in SPIHT algorithm

The basic idea of sorting all the coefficients in order of decreasing magnitude for obtaining a perfect bit assignment. As illustrated in the Figure 3, tree structure which has a baseband coefficient in root to represent a square region of the original image. The root is considered as the low pass of the region while the dependent details the better details. Three types of spatial orientation trees are considered from the root in vertical, horizontal and diagonal sub bands. In addition to the efficiency, SPIHT is simple and fast and it doesn't require any prior information.

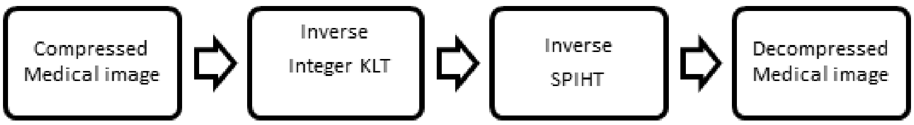


Figure 4: Proposed Decompression method

KLT is one of the competent linear based transforms which has the decorrelation capabilities. KLT over images gives high computational complexity since it uses Eigen vectors for calculation of covariance of input signal and it brings out a floating-point output value which results in making the algorithm as lossy compression method. In this paper, we proposed an Integer based KLT for medical image compression which solves the solution to achieve a lossless image compression technique based on matrix factorization. Integer KLT is used to achieve lossless decorrelation where decorrelation is a term for any process that is used to reduce autocorrelation within a signal. From matrix factorization theory [17], TERMs - three triangular elementary reversible matrices are created as a product when its factorized by the nonsingular matrix. TERM can apprehend reversible integer-to-integer transform[19].

4. Experimentation:

The resulting integer coefficients from the IKLT transform are encoded using SPIHT algorithm[20] which achieves the dependencies among the location and value of sub bands. SPIHT occupies the details LIS, LIP & LSP. list of insignificant sets, list of insignificant pixels and list of significant pixels respectively. When the complete coefficients are processed after the sorting and refinement pass, then a compressed image is generated. Figure 4 details the flow of the proposed method to achieve medical image compression.

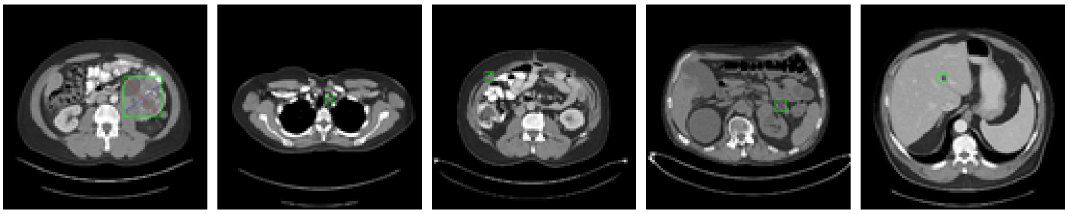
Table 1: Algorithm for image compression using Integer KLT with SPIHT encoder

Step 1:	Consider the input medical image $f(x, y)$ of size $(512 \times 512 - 8$ bits $)$
Step 2:	Input image is divided into sub images
Step 3:	Integer KL Transform find the mean of each sub image and separate it $$KL \text{ Transform } = \begin{bmatrix} KL_0 & KL_1 \\ KL_2 & KL_3 \end{bmatrix}$$ from the eigen vectors (eq 3.3)
Step 4:	Interpret the image using first eigenvector of the covariance matrix
Step 5:	Obtain the MSE of the original and encoded sub image
Step 6:	Obtain the median of all the mean square errors in the sub images
Step 7:	Relate each MSE with the median of all the mean square errors of sub images
Step 8:	RIf Sub images MSE ¡ Median of all sub images then it's a good sub image.
Step 9:	If Sub images MSE ¿ Median of all the sub images then it's a bad sub image and encode it further by changing the component $$\widetilde{y_m} = \begin{cases} b_{mm}y_m & + \left[\sum_{n=m+1}^{M} b_{mn}y_n\right]_z \quad m = 1, \ldots, M-1 \\ b_{mm}y_m, & \quad m = M \end{cases}$$
Step 10:	Repeat the step 5 till 9 using as many eigen vectors to get an integer value
Step 11:	Encode the resulting values with SPIHT encoder
Step 12:	Resulting the output image quality with PSNR, MSE, CR and CT.

Through this implementation, it has been identified that this proposed method is efficient in terms of reducing the errors. And also attains stable form. Thus, concludes that the proposed achieves a lossless image compression method using Integer KLT and SPIHT.

5. Experimentation Results

The proposed algorithm is evaluated with a set of medical images of size (512X512) and the performance analysis for the compressed images are made using (PSNR), (MSE), (CR) and (CT). The objective analysis of the proposed method is evaluated with DCT, DWT & KLT.



Input 1 Input 1 Input 1 Input 1 Input 1

Figure 5: Medical Images used for proposed compression technique

Output 1 Output 1 Output 1 Output 1 Output 1

Figure 6: Compressed medical Images obtained by proposed compression technique

Table 2,3,4 illustrates the performance comparison of PSNR, MSE, CR over individual medical images achieved with the proposed and existing techniques respectively. Fig.5 shows the input medical images considered for evaluation. Fig 6 illustrates the compressed medical image obtained after the proposed compression technique. The following sections detail the experimental investigation of the overall behavior of the proposed technique.

Table 2: Performance comparison of PSNR for various techniques with various images

Sample Images	DCT + SPIHT	DWT + SPIHT	KLT + SPIHT	Proposed Method (IKLT + SPIHT)
Image 1 (Axial abdominal 1)	40.92	39.21	43.39	46.92
Image 2 (Axial abdominal 2)	42.6	40.6	46.18	48.75
Image 3 (Hepatic hydatid abdominal)	44.73	41.07	47.8	49.9
Image 4 (abdominal with lymph)	43.37	39.86	45.9	47.14
Image 5 (Hepatic hemangioma)	42.89	38.2	45.07	45.1

Table 3: Performance comparison of MSE for various techniques with various images

Sample Images	DCT + SPIHT	DWT + SPIHT	KLT + SPIHT	Proposed Method (IKLT + SPIHT)
Image 1 (Axial abdominal 1)	3.72	4.35	2.62	2.01
Image 2 (Axial abdominal 2)	2.9	3.98	1.9	0.95
Image 3 (Hepatic hydatid abdominal)	2.7	3.6	1.17	0.81
Image 4 (abdominal with lymph)	2.61	4.71	2.21	1.74
Image 5 (Hepatic hemangioma)	2.75	4.1	2.35	2.29

Table 4: Performance comparison of CR for various techniques with various images

Sample Images	DCT + SPIHT	DWT + SPIHT	KLT + SPIHT	Proposed Method (IKLT + SPIHT)
Image 1 (Axial abdominal 1)	5.23	12.42	10.29	12.48
Image 2 (Axial abdominal 2)	10.03	11.01	9.81	11.98
Image 3 (Hepatic hydatid abdominal)	7.42	12.41	10.13	12.04
Image 4 (abdominal with lymph)	9.24	9.83	8.03	10.9
Image 5 (Hepatic hemangioma)	9.28	10.92	8.74	11.06

To achieve the best visual quality with minimum bit utilization is the major fact in image compression. PSNR is a parameter used for assessing the quality of the compressed image. It is defined as

$$\mathrm{PSNR} = 10 * \log_{10}\left(255^2/\sqrt{MSE}\right) \tag{5.1}$$

MSE in (5.1) is the mean squared error of the image defined as

$$\mathrm{MSE} = \frac{1}{N} \times \sum_i \sum_j (f(x,y) - F(x,y))^2 \tag{5.2}$$

where N denotes the total number of pixels, $f(x, y)$ states the pixel intensities of the original image and $F(x, y)$ states the intensity of pixel in the compressed image.

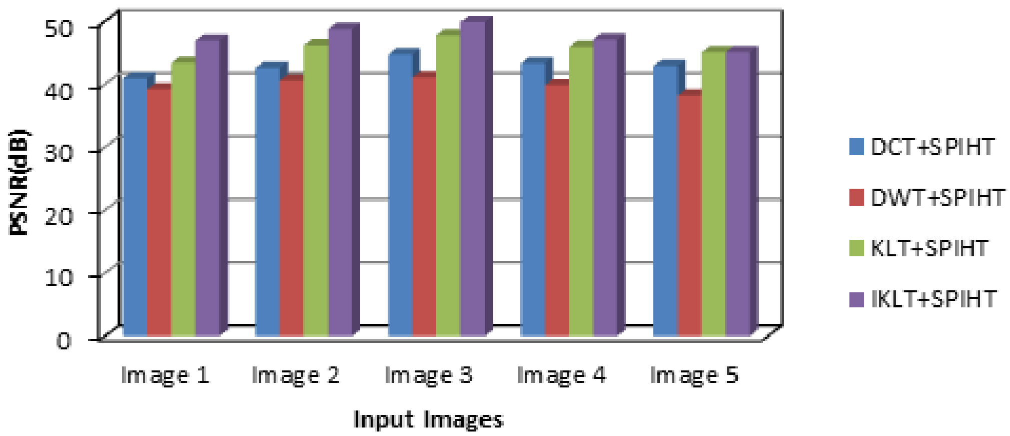


Figure 7: Comparison of PSNR's of compressed images obtained using the proposed and existing techniques

Fig 7 and Fig.8 show the average values of PSNR(dB) and MSE(dB) obtained for the several medical images as stated in Table 2 & Table 3 respectively. The result proves that the proposed compression method outperforms the existing compression algorithms such as DCT + SPIHT, DWT + SPIHT and KLT + SPIHT.

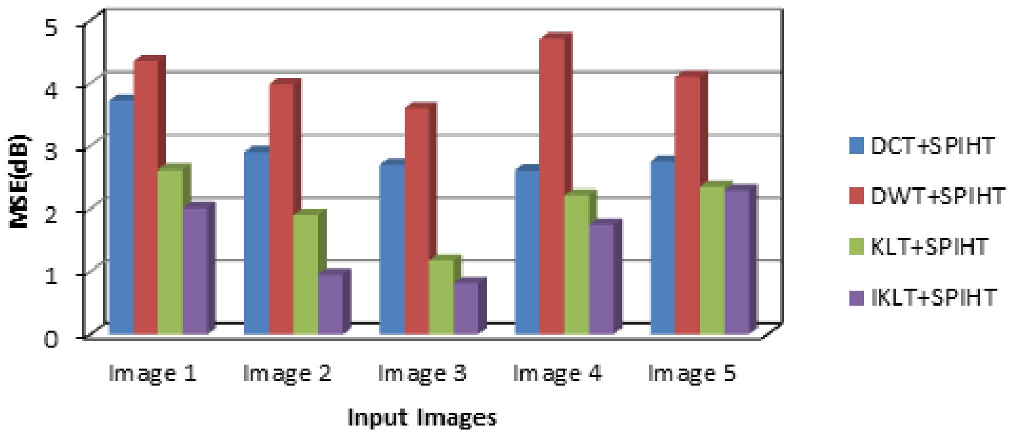


Figure 8: Comparison of MSE's of compressed images obtained using the proposed and existing techniques

$$Compression\ Ratio\ (CR) = \frac{Size\ of\ the\ Original\ Image}{size\ of\ the\ compressed\ image} \tag{5.3}$$

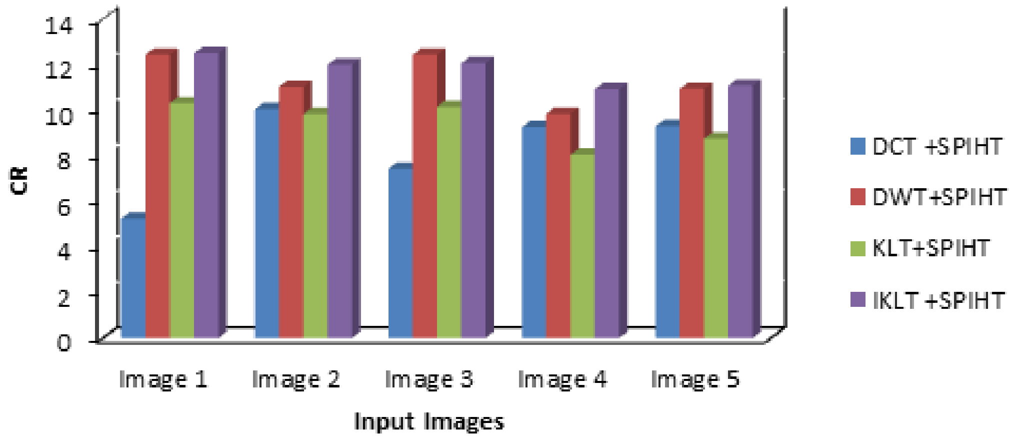


Figure 9: Comparison of CR values of compressed images obtained using the proposed and existing techniques

Fig. 9 depicts the average Compression ratio for the values given in table 4. The graph illustrates that the compression ratio achieved by IKLT transform is higher as compared with the other compression methodologies for the same set of medical images.

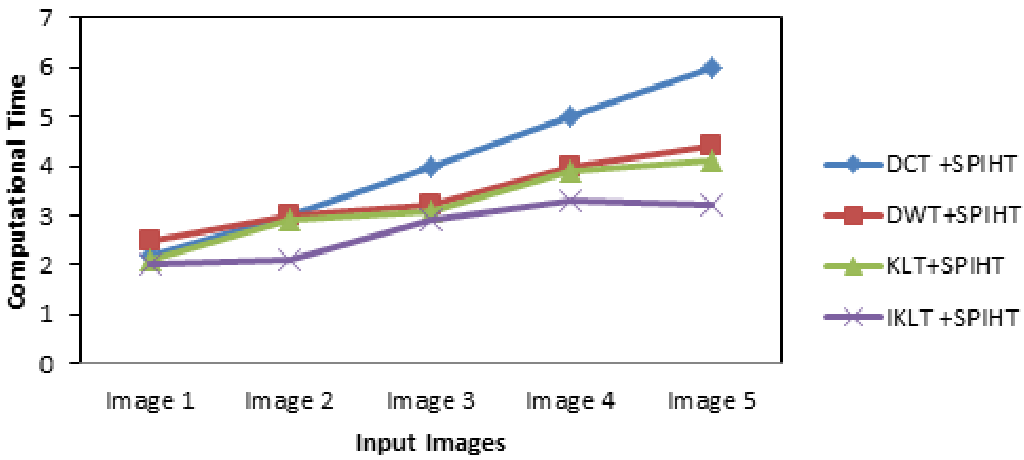


Figure 10: Comparison of Computational Time for the compressed images obtained using the proposed and existing techniques

As depicted in Figure 10 , the computational time depends on the complexity of the compression algorithm, the time taken to compute the complete process of algorithm. Algorithms were computed on a personal computer with Intel(R) i5 processor @ 2.70GHz with 16 GB RAM. The average time for processing the algorithm to compress the image using the proposed method is 0.45 sec which is very much lower as compared with the other algorithms.

6. Conclusion

Our proposed integer reversible implementation method called Integer based Karhunen-Loeve Transform (IKLT) performs better than the original linear transform calculations in terms of Energy consumption, PSNR and CR. IKLT gives an opportunity to apply a linear transform without loss in image coding when it blends with the SPIHT encoder. In the experiments, the reversible integer KLT has achieved a higher PSNR, high compression ratio and moreover a low computational time and achieves a best performance for lossless compression. Therefore, it is very possible to compress a medical image with a low computational time to achieve a high-quality output.

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