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A novel embedding technique for lossless data hiding in medical images employing histogram shifting method

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In this paper, a lossless data hiding method based on histogram shifting for MR images using Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) are presented. In this method, the algorithms are validated to hide the data in wavelet coefficients of high frequency subbands. This scheme has the advantage of comparing the DCT coefficients and the DWT coefficients which permit low distortion between the watermarked image and the original image. It also shifts a part of the histogram of high frequency subbands and embeds the data by using the created histogram zero point. To prevent the overflows and underflows in the spatial domain, caused by the modification of the DCT coefficients and the DWT coefficients, the histogram modification technique is applied. Therefore, we present a validated method to evaluate and compare the performance of DWT and DCT on task, in terms of data embedding payload and the Peak Signal to Noise Ratio (PSNR) in the medical image. A careful experimental analysis validates the method showing its superiority over the existing methods.

Keywords: Histogram shifting; lossless data hiding; DWT and DCT; MR images.

AMS Subject classification: 94A11, 68U10, 68U20, 94A08

1. Introduction

The wavelet transform was originated from Geophysics in the 1980s, for the analysis of seismic signals. It was later formulated by Grossmann *et al.* that wavelets found in signal processing and mathematics community have significant value in theoretical and medical applications. Several oriented developments took place in these fields, during the last decade. Its developments and applications still continue at a very rapid pace. The medical field has been largely benefited and revolutionized by the computer and imaging technologies. Most of this technology generates massive amounts of data that are often uncertain and imprecise. Their development of information hiding technique provides a way to protect the digital media.[28,20] These techniques may be employed to embed secret information into the image in such a way that the existence of the hidden information is imperceptible to human visual systems and the irreversibility of the technique is not admissible to some sensitive applications, such as medical imaging. For these applications, lossless data hiding is desired to extract the embedded data as well as to recover the original image.[9] In 2003, Tang *et al.* stated that the wavelet based scheme plays an important role in gray scale images for finding ribbon like shape structures and contours of equal shape.[24] In 2006, Ni *et al.* proposed the technique of image lossless data hiding algorithm using pairs of zero points and peak points in which a part of the image histogram is replaced or shifted to embed the data.[20,2] In 2007, You *et al.* proposed that a wavelet based scheme is employed for extracting a character skeleton in gray level images.[35] Initial ideas in this area were started based on the domains.[21] Subsequently, Xuan *et al.* proposed a new technique carried out in the Discrete Wavelet Transform (DWT) domain in which, the high frequency bands are chosen to embed the data bits and there achieves high payload and visual quality.[31] Mohanty *et al.* proposed the Discrete Cosine Transform (DCT) domain, which embeds the data into the bit planes of wavelet transform coefficients and prevents the pixel overflow and the underflow caused by the modification of peak points. Hence, the selected peak points shift the scale value in the image histogram and embed the data in peak points. However, both these methods are implemented in the spatial domain. The histogram distribution varies dramatically from image to image.[32] Consequently, the DWT and DCT methods achieve high embedding payload (which is referred to as capacity) and Peak Signal to Noise Ratio (PSNR) with the visual quality of the image.[18] The main objective of this paper is to compare the PSNR and embedding payload of DWT and DCT, with the capacity generated by this approach. Moreover, it can be attributed to the highly concentrated distribution shape of the histograms, where the wavelet coefficients of the frequency subbands have Laplacian like distribution, meaning that there is a peak point in the histogram around the zero point and magnitudes on both sides.[16] An important characteristic of histogram based data hiding methods is that, the existence of more histogram peaks implies higher data hiding capacity. Several peaks signify higher PSNR values in the stego images, and the gray scale values of the pixels forming the peak remain unchanged even after data embedding. Hence, the largest peak maximizes the hiding capability and minimizes the distortion.[25] Moreover, in this histogram shifting method,[29] while the shifting of histograms of frequency wavelet subbands occurs, the overflow (pixel gray scale value exceeding 255 for an 8-bit MR image) and underflow (pixel gray scale value below 0) may take place and thereby violate the lossless requirement. In order to overcome the underflow and overflow of the wavelet transform domain, the histogram modification technique is adapted.[4] It may be inferred that the wavelet transform yields better results in the histogram shifting of different medical images. In addition, the histogram approach shows a good capability of data extraction in order to get accurate values based on capacity and PSNR.[6,27]

More specifically,[31] based on our experimental works, the performance of the DWT and DCT techniques are compared and observed by maintaining a good PSNR and embedding payload for the MR images. The histogram shifting[1] achieves good strategy and high quality of the stego image. This shows the effectiveness of the proposed work.

The next section summarizes the wavelet transform (Discrete wavelets) and histogram modification, while Sec. 3 presents the lossless data hiding, based on DWT and DCT histogram shifting. Section 4 discusses the experimental results obtained from this work. Section 5 is the conclusion of this paper.

2. Discrete Wavelet Transform, Discrete Cosine Transform and Histogram Modification

2.1. *Discrete wavelet transform*

Wavelet transforms implemented on discrete values of scale and locations are called DWTs. One can obtain both redundant and nonredundant representations using the wavelet schemes. DWT is an orthogonal function "ϕ", which can be applied to a finite group of data. Functionally, it is very much like DFT. In this function, the signal is passed twice through the transformation and it remains unchanged. Both the transforms are said to be convoluted and the wavelet basis is a set of functions with variables x, k defined by a recursive difference equation given by,

$$\phi(x) = \sum_{k=0}^{m-1} \phi(2x - k). \tag{2.1}$$

The range of the summation is determined by the specific number of nonzero coefficient, m. The nonzero coefficient is arbitrary and is referred to as the order of wavelet. The value of the coefficient is not arbitrary, but can be determined by the constraints of orthogonality (ϕ) and normalization (ψ). The area under the wavelet should be uniform.

$$\sum_k C_k = 2. \tag{2.2}$$

If (2.1) is orthogonal,

$$\int \phi(x)\phi(x - k)dx = 0. \tag{2.3}$$

The orthogonality to its dilation is,

$$\int \psi(x)\psi(2x - k)dx = 0. \tag{2.4}$$

If ψ does not exist the function is given by,

$$\psi(x) = \sum_k (-1)^k C_{1-k^\phi}(2x - k), \tag{2.5}$$

which depends on $\phi(x)$. Hence,

$$\sum_k C_k C_{k-2m} = 2\delta om. \tag{2.6}$$

The above equations indicate that the sum is zero for all m not equal to zero while the sum of squares of all coefficients is two. From the equation given above, it may be concluded that,

$$\sum_k (-1)^k C_{1-k} C_{k-2m} = 0. \tag{2.7}$$

The apt method to solve the values of Eq. (2.1) is to construct a matrix of coefficient values. This is a $M \times M$ matrix. Here $M \times M$ means 256×256 matrixes of pixel values. The matrix is designated L, with entries $Lij = c2i - j$. This has an eigenvalue equal to 1. The value is an integer value of x. Once this value is known, the other values of the function, $\phi(x)$ can be generated by recursion equation. The accuracy of the function may be determined. This type of wavelet function is constrained by definition, to be zero outside a small interval. The wavelet transform, is thus made compatible to operate a set of data simultaneously.[26] This was formally called compact support. The orthogonal function "ϕ" is non-differentiable everywhere. Till date, the most popular technique for reconstruction of image is wavelet transform and is proposed by Calderbank *et al.*[36] Wavelet transform has several applications in image processing. To recover the original image, lossless wavelet transform should be used. Hence, we employ the DWT to reconstruct the original image without distortion. Also the wavelet transform can be exploited largely in this scheme for an extraordinary attribute of embedding and extraction.[34] In this transform, the data is embedded into frequency subbands (i.e. DWT coefficients). Subsequently, this scheme improves the PSNR and the embedding capacity. The DWT wavelet basis and decomposition levels for both the domains are shown in Fig. 1.

2.2. *Discrete cosine transform*

The DCT proposed by Mohanty *et al.* is an adaptive scheme, which categorizes the lossy and lossless techniques.[31] The images are represented in spatial domain and DCT transform domain. These lossy schemes undergo overflows and underflows during embedding process. During embedding, the DCT coefficients give a better resolution of the host image. However, the lossless schemes can work in the spatial domain making it suitable for all applications, since the host image is transformed into a domain that facilitates data embedding. This DCT transform, thus, gives better transform representations[7,14] and the coefficient is modified with the histogram shifting modification principle. The modified coefficients are transformed and the data are embedded in the respective frequency subbands like LL, LH and

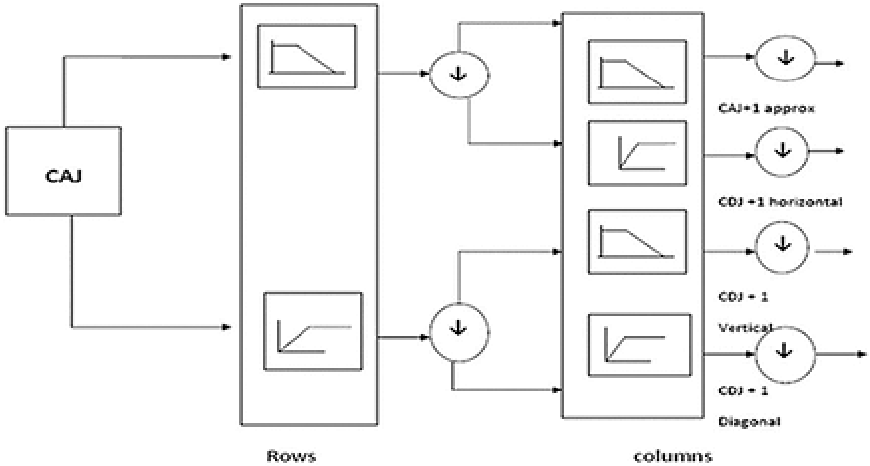


Fig. 1. Decomposition of approximation in three orientations.

finally, the perfect quality of image is reconstructed and large capacity is obtained using this histogram method.[8]

The most common DCT definition of 1-D sequence of length N is:

$$C(u) = \alpha(u) \sum_{x=0}^{N-1} f(x) \cos\left[\frac{\pi(2x+1)u}{2N}\right] \tag{2.8}$$

for $u = 0, 1, 2, \ldots, N-1$.

Similarly inverse transformation is defined as,

$$F(x) = \sum_{u=0}^{N-1} \alpha(u) c(u) \cos\left[\frac{\pi(2x+1)u}{2N}\right] \tag{2.9}$$

for $u = 0, 1, 2, \ldots, N-1$.

In both Eqs. (2.8) and (2.9) $\alpha(u)$ is defined as:

$$\alpha(u) = \sqrt{\frac{1}{N}} \quad \text{for } u = 0, \quad \sqrt{\frac{2}{N}} \quad \text{for } u \neq 0. \tag{2.10}$$

From Eq. (2.8) it is clear that for $u = 0$,

$$C(u = 0) = \sqrt{\frac{1}{N}} \sum_{x=0}^{N-1} f(x). \tag{2.11}$$

The first transform coefficient is the average value and is referred to as DC coefficient.

The plot of

$$\sum_{x=0}^{N-1} \cos\left[\frac{\pi(2x+1)u}{2N}\right] \tag{2.12}$$

for the function $f(x)$ and $\alpha(u)$ and other waveforms ($u = 1, 2, 7$) called cosine basis function. In DCT, the pixel values in one frame can be used to predict the pixel

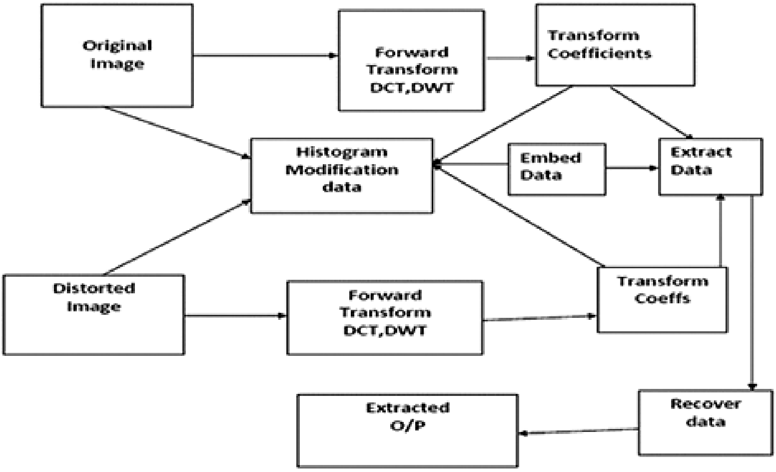


Fig. 2. Block diagram of data hiding: Data embedding and data extraction.

values in the adjacent frame. These wavelet coefficients from the database of medical images, at different decomposition levels, and the pixels with wavelet basis, focus the image as a set of transform coefficient statistics.[15,5] The images are decomposed and transformed using DWT/DCT and the coefficients are applied to the histogram modification. After the data are modified, they are embedded and made to undergo the extraction process. The extracted data are retrieved finally.[17,15] This wavelet basis gives better resemblance to the PSNR[23] and the embedding capacity. The DCT domain helps in reconstruction of the original image as shown in Fig. 2.

2.3. *Histogram modification*

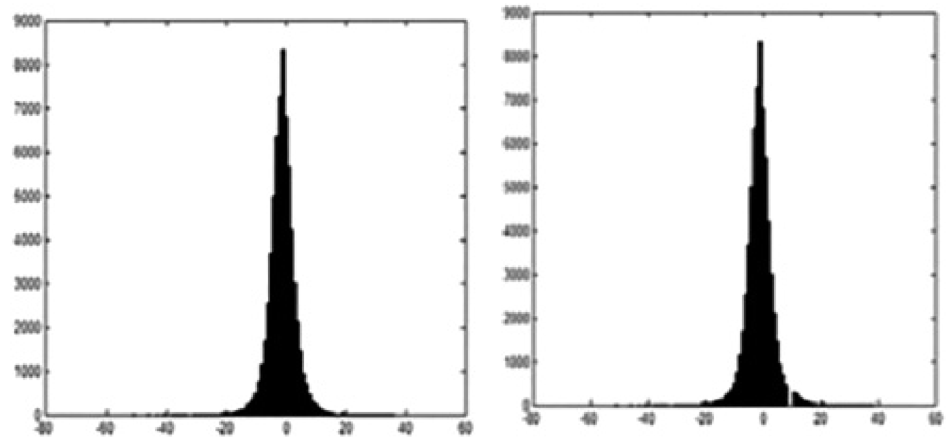
For a given medical image, after the data is embedded as DWT and DCT coefficients, it is possible to cause the overflow and underflow. This indicates that after the DWT, the pixel gray scale values $[0, 255]$ of marked medical image may exceed the upper bound (255 for 8-bit gray scale image) and the lower bound (0 for 8-bit gray scale image).[30,31] The histogram modifications are adapted to prevent the overflow and underflow and to narrow the histogram from both the sides. Moreover, the histogram is also used in sharpening the edges of images to enhance the quality.[24] The informations will be embedded into the cover media (image) together with the overhead and recovery of original image is done successfully.[19]

3. Lossless Data Hiding Based on Discrete Wavelet and Discrete Cosine Histogram Shifting

3.1. *Introduction to wavelet histogram shifting*

The histogram shifting takes care of the specifities of the medical image content by applying to the image that can be watermarked in different fashion and the data embedding and extraction remain synchronized in order to achieve better PSNR and capacity.[11] In this scheme, wavelets have been successfully used in image enhancement analysis and histogram shifting.[33] These wavelets are represented with good resolution, in different frequency subbands. The characteristic feature of histogram shifting is that it provides a compact representation of the image.[25] Hence, the wavelet transformed domain is believed to be more optimal than the spatial domain. The wavelet coefficients have been distributed in high frequency subbands. The histograms of high frequency subbands, referred to as wavelet histograms, are intended in this paper.[29] There are two axes in histograms, one is horizontal axis and the other is vertical axis. The horizontal axis represents the wavelet coefficients and vertical axis represents the occurrence of the number of corresponding wavelet coefficients.

We consider a simple example as shown in Fig. 3(a) for our discussion. This demonstrates the principle of data embedding using histogram shifting. Figure 3(a) shows the original histogram shifting of Discrete Wavelet high frequency subband.[13] In Fig. 3(b), a zero point (no other coefficients in this subband assume this specific value, M) is created. This implies that we shift the part of the histogram[3] with values larger than M toward the right-hand side by one unit. The original M value now becomes $M+1$, while the original $M+1$ becomes $M+2$ and so on. The part of the histogram[1] with values less than and equal to M remains unchanged. In data embedding technique, the DWT and DCT coefficients in the high frequency subband are scanned. Primarily, when the DWT coefficient of value M is encountered and the embedded bit is 1, the coefficient value will be added by 1 i.e. it becomes $M+1$. If the embedded bit is 0, the coefficient value remains to be M. The data extraction is in fact, the reverse process of data embedding.[17] When the DWT



(a) (b)

Fig. 3. Wavelet histogram shifting. (a) Original histogram and (b) histogram after a zero point is created.

coefficients of the high frequency subbands i.e. HL, LH and HH of value $M+1$ is met, bit 1 is extracted and the coefficient value reduces to M. Consecutively, if the value of M is met, bit 0 is extracted. Following the extraction of all data, a specific region of histogram, equal to or larger than $M+2$, needs to be shifted toward the left side by one unit.[23] It is known that the histogram shifting can also be carried out on the left-hand side. Evidently, the occurrence of the number of coefficients having the value M in the histogram is the payload. The wavelet coefficients, encountered in the embedding process, are controlled by using a key in order to make the hidden data secure. The data embedding and the data extraction process elucidated above are summarized.[17,33] As shown in Fig. 3, we shift or move the histogram, starting from the value $M+1$ towards the right-hand side one by one without making the value of $M+1$ empty i.e. by generating a zero point at $M+1$ histogram. Therefore, in accordance with the embedded bit sequence, we keep the coefficients of M constant, by not changing their embedded values. During the data retrieval, we extract a bit 0 from those coefficients with value M. The same bit is repeated for those coefficients having a value of $M+1$. The value of coefficients may also be reduced from $M+1$ to M. After all hidden bits have been extracted, the part of the histogram larger than $M+1$, is shifted towards the left-hand side by one unit.[17,22] In the data embedding process, the DWT and DCT coefficients of the marked image are obtained. Furthermore, the original cover image should be recovered. As the histogram of DWT high frequency subbands obeys the Laplacian-like distribution, experiments confirm that our histograms offer substantial steady improvement in its accuracy.[1] It may be inferred that, based on the algorithm, we can embed the data on both sides of the histogram until all the to-be embedded bits are embedded.[7]

3.2. *Data embedding algorithm*

For a given MR image, the embedding and extracting algorithms are presented. Assume that there are N bits to be embedded into a frequency subband of DWT and DCT. The data embedding process is carried out in the following manner:

(1) Set a peak. The number of high frequency wavelet coefficients in [−P, P] be greater than N.
(2) In the wavelet histogram, shift the histogram to the right-hand side by one unit to leave a zero point at the peak value. Subsequently, embed the data in this point.
(3) If the data to be embedded remains let peak $=-$peak. Move the histogram to the left-hand side, by one unit, to leave a zero point at the value $(-\text{peak}, -1)$. Subsequently, the data are embedded at the point.
(4) When the entire data have been embedded, stop the embedding process and record the peak P. Else, go back to step (2) to continue the embedding of the remaining data.

3.2.1. *Data extraction algorithm*

The data extraction is the reverse of data embedding. Without any loss, assume that the data embedding process is positive. The data extraction steps are as follows:

(1) Set P (peak).
(2) Decode the value P and the value $P + 1$. Extract all the data until $P + 1$ becomes a zero point. Move the DWT and DCT coefficients of the histogram toward the left-hand side by one unit, to eliminate or cover the zero point.
(3) If the amount of extracted data is less then set $P \leftarrow -P - 1$, continue to extract the data until $(P - 1)$ becomes a zero point. Then, move the histogram (less than $P - 1$) to cover or eliminate the zero point.
(4) If all the hidden bits have been extracted, stop the process. Else, set $P \leftarrow -P$ and retrace to step (2), to continue the data extraction.

3.3. *Detailed algorithm*

The embedding and extraction algorithm for medical MR images were presented clearly for DWT and DCT. Here the bits are embedded into the frequency subband of DWT and DCT. First the embedding process takes place for high frequency coefficients greater than N. In the wavelet technique, we shift the histogram to right-hand side and embed that value. Subsequently, we move the histogram to the left-hand side and embed the value as $(-)$. The data embedded causes overflow and underflow and thus indicates that the pixel gray scale values of marked medical images may exceed the upper bound gray scale image in order to recover the original data. The data extraction is just the reverse of data embedding process. Without any loss we have to decode all the values and eliminate the zero point. The extracted data will be less than the peak values. Once all the data are extracted we say that the recovered data is obtained without any loss.

4. Experimental Results and Their Comparison

In this section, experiments are carried out to test the performance in terms of capacity and PSNR as shown in Fig. 4. The image to be embedded is of the dimensions 256×256. In all our experiments, the quality and recovery of the image have been done perfectly. Data embedding and extraction are done precisely. The proposed method has been implemented using Mat lab, and tested with the database of different medical images.[10] The extraction and recovery of the original image, with respect to PSNR, in the proposed method are better as compared to the performance measures of the existing work. Moreover, the maximum number of bits embedded for DWT is 15,336 and the maximum number of bits embedded for DCT is 10,000, the difference between the original and the recovered image is 0. Thus the bits embedded for DWT are more than that of DCT. The PSNR value is high for those medical images and the visual quality is still acceptable. The

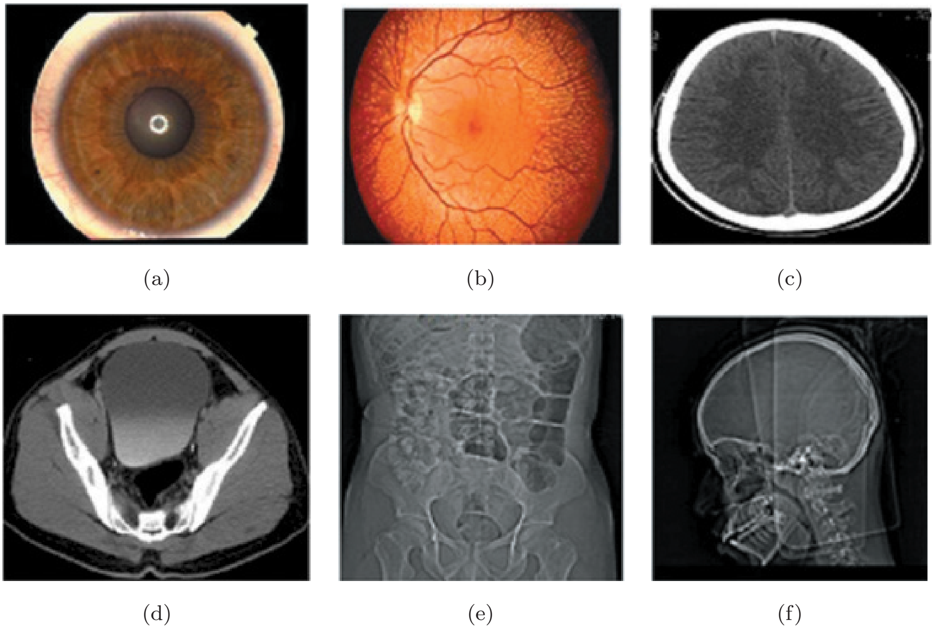


Fig. 4. PSNR and capacity of marked images with a payload of 0.5 bpp (a) iris: 58.9 dB and 85×10^4, (b) retina: 49.8 dB and 80×10^4, (c) brain: 56.7 dB and 70.5×10^4, (d) abdomen: 56.6 dB and 75.5×10^4, (e) stomach: 54.1 dB and 70.5×10^4 and (f) skull: 53.5 dB and 69.5×10^4.

medical images of iris, brain and abdomen each of 256×256 pixels are reported here and the PSNR vs. embedding capacity are shown in Tables 1 and 2 for DCT and DWT, which shows the difference between the two transforms. Furthermore, the embedding algorithm and the extraction algorithm are tested and compared.[12]

Table 1. Experimental results of PSNR and capacity for DWT.

Medical images	PSNR (db)	Embedding capacity
Img(a)	57.9	85,522
Img(b)	54.8	60,389
Img(c)	55.8	70,555
Img(d)	56.7	80,656
Img(e)	54.1	75,633
Img(f)	53.5	70,533

Table 2. Experimental results of PSNR and capacity for DCT.

Medical images	PSNR (db)	Embedding capacity
Img(a)	47.9	80,522
Img(b)	44.8	55,389
Img(c)	45.8	65,555
Img(d)	46.7	75,656
Img(e)	44.1	70,633
Img(f)	42.2	65,566

Tables 1 and 2 show the PSNR and embedding capacity for different medical images such as — iris, brain, retina and abdomen — using DWT and DCT transform techniques. It indicates that the increase of the PSNR does not always lead to the increase of payload. When payload is smaller, we can choose larger peak. During data embedding, the lesser number of coefficients are altered and the resultant PSNR and capacity are found to be high for DWT and moderate for DCT technique. Hence, a great improvement is observed in this approach.[3] It has to be noted that the performance comparison between these methods has been

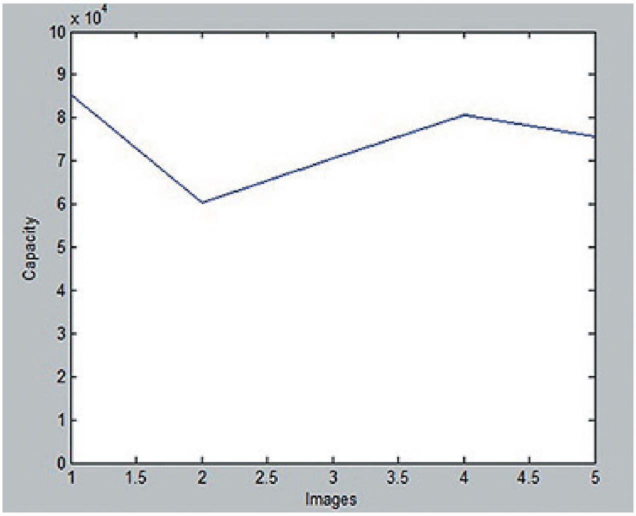


Fig. 5. Capacity vs. medical images with data hiding using histogram shifting in the Differential Wavelet Transform domain.

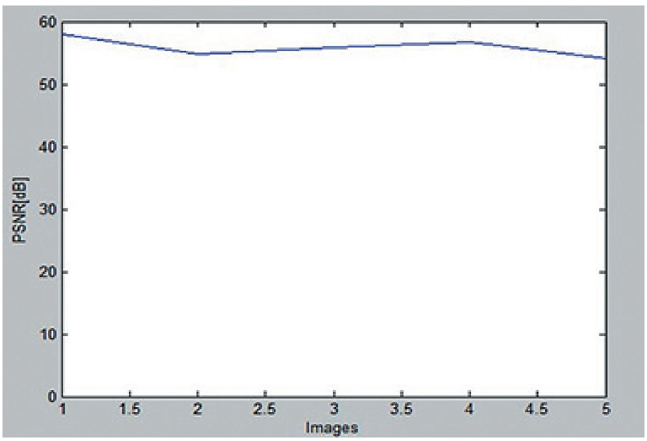


Fig. 6. PSNR vs. different medical images with data hiding using histogram shifting in the Differential wavelet transform domain.

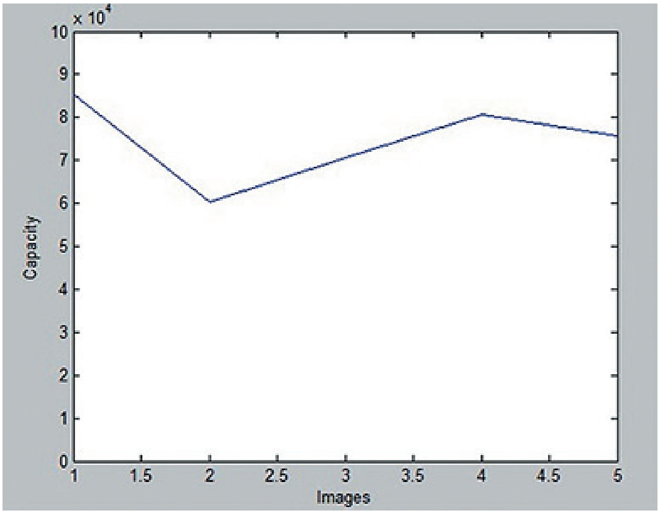


Fig. 7. Capacity vs. medical images with data hiding using histogram shifting in the DCT domain.

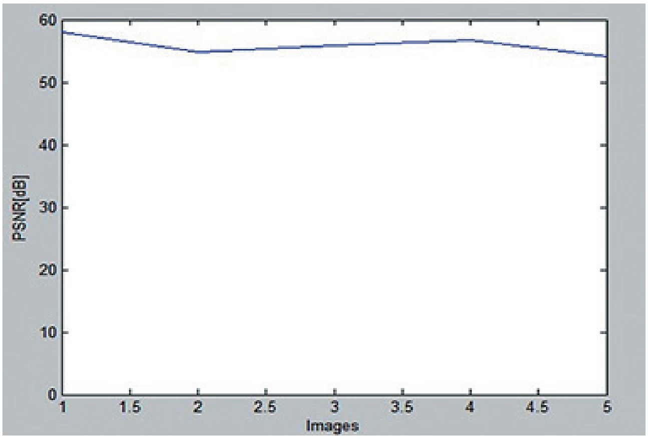


Fig. 8. PSNR vs. medical images with data hiding using histogram shifting in the DCT domain.

experimentally done for PSNR and capacity. The PSNR vs. embedding capacity for DWT is superior[31] to that of DCT and the experimental results are reported in this paper. The performances, in terms of PSNR vs. embedding capacity, are shown graphically in Figs. 5–10, respectively.

The graphs, clearly depicts the corresponding PSNR vs. embedding capacity for different values of medical images with respect to quality, the images used and the algorithms implemented. The capacity CPSNR performance of DWT and DCT of our algorithm reveal the progress made by our method. The graphs show that the high PSNR value for DWT is 57.9 and capacity is 85,522 and for DCT PSNR value is 47.9 and capacity is 80,522. Therefore, the PSNR and capacity differ for different

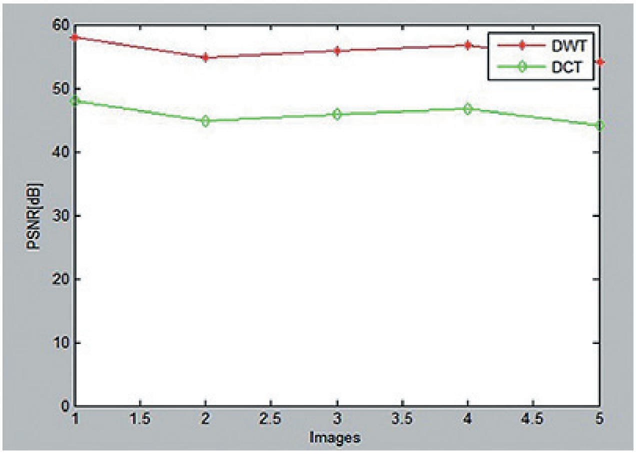


Fig. 9. Comparison of PSNR vs. medical images with data hiding using histogram shifting in the DWT and DCT domains.

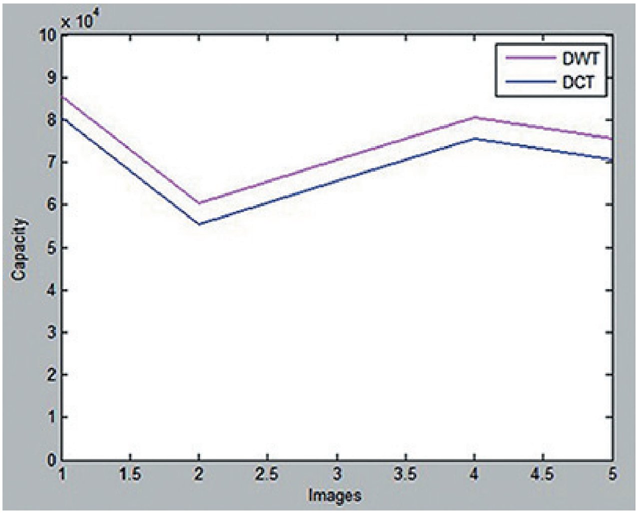


Fig. 10. Performance comparison of capacity vs. medical images with data hiding using histogram shifting in the DWT and DCT domains.

medical images as shown above. Hence, it may be inferred that, the capacity at PSNR is higher for DWT, when compared with the embedding capacity at PSNR for DCT.

4.1. *Performance evaluation*

In order to evaluate the extracted data of medical images in both DWT and DCT domains, the images are recovered without loss successfully. The image enhancement analysis and the characteristic features of shifting provide the compact representation of image. The wavelet coefficients are distributed in frequency subbands in order to determine a futuristic approach. The images are represented in transform domain so that it is applicable for all applications which facilitate the data embedding. These coefficients of medical images of pixel values $[0, 255]$ after decomposition form the coefficient statistics. This wavelet basis gives better PSNR and embedding capacity. Thus this approach clearly proves the quality of recovered data with respect to PSNR and capacity. The performance evaluation of the proposed medical image is reported in metrics of charts. The demonstrated results show the images in the data set with respect to PSNR and capacity.

5. Conclusion

Wavelet transforms have numerous applications such as atmospheric turbulence, analysis of transient phenomenon, identification of scale invariant symmetrics, data compression, noise reduction and feature extraction. We have studied, in detail, the wavelet representation of an efficient data hiding approach. The embedded data achieved a higher degree of quality with respect to histogram shifting. Calderbank theory has already established that it is an excellent alternative to provide reliable recovery of images and also ensures a fine degree of security. DWT and DCT are widely used mechanisms for frequency transformation. The detailed analysis and experimental results prove that the embedding approach, along with the histogram technique, does not deteriorate under any aspect and also shows the effectiveness of the method. Moreover, it is tested using MATLAB 7.8 version. The comparison of these two wavelet transforms implementation has proved higher degree of quality. By comparing the two methods, we have successfully designed the performance analysis of DWT and DCT with respect to PSNR and embedding capacity. Among this, DWT has been found to have higher PSNR and capacity. The performance result in terms of PSNR for different medical images reveals that they are enhanced in the proposed algorithm than the existing methods. Moreover, better image quality is obtained in the same payload. Future researches may be directed to investigate more wavelet types for further improvement on data hiding capacity and PSNR, using histogram shifting technique and other real time applications.

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