Adaptive Image Steganography Based on Dual Tree Discrete Wavelet Transform

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Abstract: Steganography gained importance in the past few years due to the increasing need for providing secrecy in an open environment like the internet. With almost anyone can observe the communicated data all around, steganography attempts to hide the very existence of the message and make communication undetectable. The characteristics of the Dual Tree Wavelet Transform that provides shift invariance and offers better directional selectivity makes it a better choice for data hiding over the classical discrete wavelet transform. For achieving the security and robustness, the original message is first converted into binary cell array with the help of self-synchronizing variable length codes, viz., T-codes before the embedding. The experimental results show that the dual tree complex wavelet transform is better option than the Wavelet, Wavelet-like transform, i.e., Slantlet transform and Double Density Dual Tree DWT for data hiding in terms of visual quality and embedding capacity, though poor to external attacks such as Gaussian. In this paper, optimize the two main requirements by proposing a novel technique for hiding data in digital images by combining the use of adaptive hiding capacity function that hides secret data in the integer wavelet coefficients of the cover image with the optimum pixel adjustment (OPA) algorithm. The coefficients used are selected according to a pseudorandom function generator to increase the security of the hidden data.

Keywords: Steganography, Adaptive Algorithm, Spatial Domain, DWT, SLT, DD DT DWT.

I. INTRODUCTION

The discrete wavelet transform (DWT) is considered to be an important tool for data hiding techniques. There are applications that demand high capacity, e.g., in the advance research on network transmission security and lossless embedding such as in military, legal and medical imaging domains. There exists steganographic algorithm based on integer wavelet transform that provides better embedding capacity and better imperceptibility than the earlier used transforms such as DCT. DCT remained famous domain of embedding as it was the major compression technique in earlier JPEG compression technique. Wavelet transform replaced the DCT in the JPEG 2000 and also found to be better option than DCT in terms of embedding capacity and robustness. However, DWT lacks directional selectivity for diagonal features and shift invariance. The dual tree complex wavelet transform (DT-CWT) has a modest amount of redundancy, but it provides shift invariance and good directional selectivity.

The 2-D DT-CWT is based on two distinct scaling functions and two distinct wavelets, whereas Double-Density DWT is based on a single scaling function (low pass) and two distinct wavelets (high pass). On the application of 2-D DD DWT, the cover image is decomposed into nine sub-bands labeled LL, LH1, LH2, H1L, H1H1, H1H2, H2L, H2H1, H2H2, respectively. The Double Density Dual-Tree DWT (DD DT DWT) possesses simultaneously the properties of DT DWT and DD DWT. The structure of DD DT DWT consists of two oversampled iterated filter-bank that operate in parallel. Each row of the cover image is first subjected to 1-D DD DT DWT decomposition in which one is real decomposition that uses the real component of DD DT DWT and the other is an imaginary decomposition. After the 1-level decomposition obtains four times wavelets than the ordinary 2-D DD DWT decomposition.

In this proposed a high capacity data hiding technique based on the four transforms, viz., Wavelet (wavepdf97), Slantlet, Double Density Dual Tree DWT and Double Density Dual Tree Complex Wavelet, respectively.
embed data into an insensitive Wavelet/Slantlet/DTD-CWT sub-bands using the modified LSB method. The embedding capacity can reach to ¾ of the cover image (grayscale) in Wavelet and Slantlet domains and 6/7 and more of the cover image (grayscale) in DD DT-CWT domain. The proposed algorithms are implemented in Matlab 7.0 using 256 x 256 size images. Experimental results show that the DD DT-CWT method has not only higher capacity but also better visual quality than other three methods, viz., Wavelet (wavcdf97), Wavelet-like transform (i.e., Slantlet) and DD DT DWT. This proposed improved high capacity steganographic technique can be applied to e-government, e-business, e-law enforcement, military system and e-medical system.

The classical discrete wavelet transform (DWT) provides a means of implementing a multi-scale analysis, based on a critically sampled filter bank with perfect reconstruction. It has been shown to be very effective both theoretically and practically [3] in the processing of certain classes of signals, for instance piecewise smooth signals, having a finite number of discontinuities. But, while decimated transforms yield good compression performance, other data processing applications (analysis, denoising, and detection) often require more sophisticated schemes than DWT. Steganography is the art and science of hiding secret data in Plain sight without being noticed within an innocent cover data so that it can be securely transmitted over a network. The word steganography is originally composed of two Greek words steganos and graphia, which means "covered writing". The use of steganography dates back to ancient times where it was used by romans and ancient Egyptians. The interest in modern digital Steganography started by Simmons in 1983 [1] when he presented the problem of two prisoners wishing to escape and being watched by the warden that blocks any suspicious data communicated between them and passes only normal looking one. Any digital file such as image, video, audio, text or IP packets can be used to hide secret message. Generally the file used to hide data is referred to as cover object and the term stego-object is used for the file containing secret message.

Among all digital file formats available nowadays image files are the most popular cover objects because they are easy to find and have higher degree of distortion tolerance over other types of files with high hiding capacity due to the redundancy of digital information representation of an image data. There are a number of steganographic schemes that hide secret message in an image file; these schemes can be classified according to the format of the cover image or the Method of hiding. Here have two popular types of hiding methods; spatial domain embedding and transform domain Embedding.

The Least Significant Bit (LSB) substitution is an example of spatial domain techniques. The basic idea in LSB is the direct replacement of LSBs of noisy or unused bits of the cover image with the secret message bits. Till now LSB is the most preferred technique used for data hiding because it is simple to implement offers high hiding capacity, and provides a very easy way to control stego-image quality [2] but it has low robustness to modifications made to the stego-image such as low pass filtering and compression [3] and also low imperceptibility. Algorithms using LSB in grayscale images can be found in [4, 5, 6]. The other type of hiding method is the transform domain techniques which appeared to overcome the robustness and imperceptibility problems found in the LSB substitution techniques. There are many transforms that can be used in data hiding, the most widely used transforms are; the discrete cosine transform (DCT) which is used in the common image compression format JPEG and MPEG, the discrete wavelet transform (DWT) and the discrete Fourier transform (DFT).

II. EMBEDDING DOMAIN

In designing steganographic algorithm, special consideration is given to the domain in which the embedding will take place. No doubt, frequency domain have shown to Image Steganography Based on Complex Double Dual Tree Wavelet Transform Sushil Kumar and S. K. Muttoo be a better option than the spatial domain for steganographic algorithms in terms of high capacity, visual quality and robustness [4], [5]. Some of the transform domains already used in steganography are Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), Discrete (Haar/cdf(2,2)) Wavelet Transform (DWT), Directional transforms such Curvelents, Contourlets etc. and Wavelet-like Transforms such as Slantlet Transform (SLT). The contourlets are introduced by M.N. DO and M. Vetterli [6], Navas et al. [7] have described data hiding approach based on contourlet in medical images.

The slantlet transforms were introduced by Alpert et al. [8] and are described explicitly by Ivan selesnick [9]. Panda et al. [10] have shown that SLT possesses better energy compaction properties than DWT. Maitra and Chatterjee [11] have used SLT in the intelligent system for magnetic resonance brain image classification. Sushil Kumar and S.K.Muttoo [12]-[14] have also shown that SLT further provides a much better approximation of the Human Visual System (HVS) than the DWT. However, DWT and SLT have their inability to differentiate between opposing diagonal features, i.e., have poor directional selectivity and lack of shift invariance. Selesnick [15] has shown that Complex Wavelet Transform (CWT) has the advantage of excellent shift invariance at the cost of 2:1 redundancy for 2-D signals. The DT DWT not only
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overcomes the problem of poor directional selectivity in DWT, but can also discriminate between opposing diagonals with six different sub-bands oriented at 150, 750, -150, -750, and – 450.

The one of the major requirement of any steganographic algorithm is imperceptibility. So it is necessary to limit the distortion applied to each individual coefficient of the transform decomposition. One of the solutions suggested by researchers is the use of error correcting codes but it increases the size of message to be embedded. The other solution may be to find the encoding scheme that minimizes the bit conversion while embedding the secret message. This method increases the computations. One may also use visual tests such as Just Noticeable Distortion (JND) profile. In the proposed algorithm used Self-synchronizing variable length codes, T-codes which have shown to be a better encoding scheme than a popularly known Huffman’s coding [16], [17].

Generally wavelet domain allows us to hide data in regions that the human visual system (HVS) is less sensitive to, such as the high resolution detail bands (HL, LH and HH), Hiding data in these regions allow us to increase the robustness while maintaining good visual quality. Integer wavelet transform maps an integer data set into another integer data set. In discrete wavelet transform, the used wavelet filters have floating point coefficients so that when the hide data in their coefficients any truncations of the floating point values of the pixels that should be integers may cause the loss of the hidden information which may lead to the failure of the data hiding system [II].

![Wavelet Decomposition Diagram](image)

**Figure I.** (a) Original image Lena and how it is decomposed using wavelet filters (b) One level of 2DDWT decomposition and (c) One level of 2DIWT decomposition

To avoid problems of floating point precision of the wavelet filters when the input data is integer in digital images, the output data will no longer be integer which doesn’t allow perfect reconstruction of the input image [12] and in this case there will be no loss of information through forward and inverse transform [II]. Due to the mentioned difference between integer wavelet transform (IWT) and discrete wavelet transform (DWT) the LL subband in the case of IWT appears to be a close copy with smaller scale of the original image while in the case of DWT the resulting LL subband is distorted as shown in 'Fig. I'. Lifting schemes is one of many techniques that can be used to perform integer wavelet transform [13] it is also the scheme used in this paper. The following is an example showing the lifting schemes to obtain integer wavelet transform by using simple truncation and without losing invertibility [13].

### III. PROPOSED ALGORITHM

In the proposed Algorithm DD DT DWT/DD DT-CWT based embedding algorithm in which the secret message is embedded in the insensitive frequency coefficients using modified LSB approach. LSB steganography is the simplest steganographic technique used in popular steganographic tools such as S-Tools, Steganos and StegoDos, where embedding is done in the spatial domain. The sequential LSB has a serious security problem [18] whereas random or modified LSB in which secret message can be randomly scattered in stego-images provides an improvement over the steganographic security. The basic idea of LSB embedding is to embed the message bit at the rightmost bits of pixel value so that the embedding method does not affect the original pixel value greatly. The formula for the embedding is as follows:

$$x' = x - x \mod 2^k + b$$

where $k$ is the number of LSBs to be substituted. The extraction of message from the high frequency coefficients is given as:

$$b = x \mod 2^k$$

The proposed algorithm proceeds as follows:

**Step1.** Obtain the secret data by applying best T-codes to the given input text/message. An encoded key is generated.

**Step2.** Decompose the cover image low and sub-bands (viz., LL, HL, LH and HH) by applying 2-D DWT/SLT/DD DT DWT/DD DT-CWT.
Step 3. Approximate/Normalize the frequency coefficients to integers using a threshold value, usually 0.8.

Step 4. Embed secret data in the middle and high frequency bands (LH, HL and HH) using the modified LSB method.

Step 5. Obtain the stego-image by taking the inverse transform to the modified image.

The extraction method is the reverse method of embedding algorithm. It consists of the following steps:

Input: stego-image, encoded-key, stego-key
Output: original message

Step 1. Decompose the stego-image into low and high sub-bands using the transforms Wavelet/Slantlet/DDT/DWT/DTCWT.

Step 2. Extract the secret message using the stego-key used in embedding technique.

Step 3. Obtain the original message by decoding the secret message using T-decoding algorithm and encoding key.

IV. PERFORMANCE EVALUATION OF IMAGE AND VIDEO DENOISING

The implementation of 2-D ADDWP is based on a wavelet toolbox [7] that contains Matlab codes of 2-D DDWT. The nearly symmetric orthogonal Farras filters are used for the first level decomposition and the 6-tap Q shift filters (Table 2 in [11]) are used for the remaining stages. The CDF 9/7 filters are used for anisotropic decomposition. Test images are 4-level transformed with 2-D DDWT while test sequences are 3-level transformed with 3-D DDWT. All the experiments are conducted on a laptop with an Intel(R) Core(TM) 2 Duo 2.0-GHz CPU and 2.0-GB RAM.

In the evaluation of denoising performance, two test images of size 512 × 512, i.e., Barbara and Lena, and six test sequences, i.e., News (CIF), Foreman (CIF), Football (CIF), Mobile (CIF), Garden (SIF), and Tennis (SIF), are employed. The first 80 frames of these sequences are taken for experiments, unless otherwise stated. Noisy images and sequences are obtained by polluting the clean ones with white Gaussian noise under noise level \( \sigma_{R} = 10, 15, 20, 25, \) and 30. Pixel values of noisy images, noisy sequences, and denoised ones are clipped to the range of [0 255]. Denoising performance is measured by PSNR:

\[
PSNR = 10 \log_{10} \left( \frac{255^2}{MSE} \right),
\]

where MSE is the mean squared error between the denoised signal \( \hat{x} \) and original signal \( x \) of \( M \) samples: \( MSE = \frac{1}{M} \sum_{i=1}^{M} (x_i - \hat{x}_i)^2 \). For denoised video, PSNR is calculated by averaging the PSNRs of all frames.

Before comparing the denoising performance of our method with other methods, first investigate the influence of different settings, i.e., different basis selection algorithms and different windows sizes for local variance estimation, on denoising performance and then select the most reasonable one by jointly considering computational complexity and denoising performance. Here also compare the proposed adaptive wavelet packets with two fixed wavelet packet decomposition structures on DDWT sub-bands using the same denoising algorithms.

A. Three Aspects on Denoising Performance

1) Optimal vs. Greedy Basis Selection: Compare the greedy basis selection algorithm with the previous developed optimal basis selection algorithm in [4]. As shown in Table II, the greedy basis selection is about five times faster than

Fig. 2. (a) Empirical joint real-part-imaginary-part histogram and (b) the fitted probability density function.

Fig. 3. (a) Empirical plot of the shrinkage function with the adaptive threshold T2 for Barbara under the noise
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level $\sigma_n = 10$ and (b) section lines of the shrinkage surface in (a) at different fixed value of the real part.

the optimal basis selection for 2-D case, and is about 30 times faster for 3-D case. The costs of ADDWP coefficients are reduced up to 24.67% compared with original DDWT coefficients. The cost reduction is more significant for images (videos) with complicated textures (high motion activities), such as Barbara (Football and Tennis), and is less significant for those with smooth regions (low motion activities), such as Lena (Mobile). It can be seen that ADDWP with greedy basis selection significantly reduces the computational complexity, but only slightly compromises the cost. The increase of coefficient cost of the greedy basis selection method is within 1.5% compared with the optimal one. Image and video denoising results associated with the two basis selection algorithms are tabulated in Table III. Being consistent with the slight increase of coefficient cost, the denoising results produced by ADDWP with greedy basis selection are slightly lower than, but very close to, those produced by ADDWP with optimal basis selection. For both image and video denoising, the performance loss is within 0.25 dB. Therefore, the greedy basis selection for ADDWP explained in the following experiments. In these comparisons, the windows size for local variance estimation for image denoising is $3 \times 3$ and that for video denoising is $3 \times 3 \times 3$. The above conclusions also can be drawn from

experiments with different window sizes.

2) Windows Size in Local Variance Estimation:

To consider the non-stationary characteristics of images, a neighborhood $N_i$ of each coefficient $y_i$ is involved to estimate the local variance. A $n \times n$ window with the current coefficient as its center is adopted as the neighborhood. Image and video denoising performance of the proposed method with different windows sizes are shown in Fig. 5. For image denoising, a smaller window is beneficial to images with complicated texture, such as Barbara, and a larger window is more suitable.

### Table II

**Evaluation of Running Time and Coefficient Cost for Optimal and Greedy Basis Selection Algorithms. The Unit of Running Time (Magnitude Order of Coefficient Cost) in 2-D Case Is Second (10^6) While That in 3-D Case Is Minute (10^8).**

<table>
<thead>
<tr>
<th>Method</th>
<th>2-D ADDWP</th>
<th>3-D ADDWP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Barbara</td>
<td>Lena</td>
</tr>
<tr>
<td>Time Optimal</td>
<td>3.32</td>
<td>3.37</td>
</tr>
<tr>
<td>Greedy</td>
<td>0.75</td>
<td>0.42</td>
</tr>
<tr>
<td>Cost Optimal</td>
<td>3.239</td>
<td>1.918</td>
</tr>
<tr>
<td>Greedy</td>
<td>2.838</td>
<td>1.896</td>
</tr>
<tr>
<td></td>
<td>2.842</td>
<td>1.901</td>
</tr>
</tbody>
</table>

For images with smooth regions, such as Lena found that the window size of $5 \times 5$ achieve good tradeoff for most of natural images among window sizes of $3 \times 3, 5 \times 5, 7 \times 7, 9 \times 9$. For video denoising, the window size of $3 \times 3 \times 3$ provides the best performance among four different sizes, i.e., $3 \times 3 \times 3, 5 \times 5 \times 5, 7 \times 7 \times 7, 9 \times 9 \times 9$. Therefore, Here use $5 \times 5$ for image denoising and $3 \times 3 \times 3$ for video denoising in the following experiments.

3) Decomposition Structures of Wavelet Packets:

Before the adaptive wavelet packets, two fixed wavelet packet decomposition structures on DDWT have been proposed: the full wavelet packet for image deconvolution in [3] and the fixed anisotropic decomposition structure for image denoising in [4]. In the full wavelet packet, all DDWT sub bands are iteratively decomposed until the resulting sub bands have the same size as the low-pass sub band. In the fixed anisotropic decomposition structure, for each DDWT sub band in the low frequency ends in any direction (the vertical or horizontal), the sub band will be further decomposed in this direction until the maximum decomposition level is reached. Both these decomposition structures are special cases of the proposed adaptive wavelet packets to compare the denoising performance of the three wavelet packet decomposition schemes. In [4], the simple it is used and thus the performance is far below the proposed method. For fair
comparison, the proposed denoising method is applied to all the three wavelet packets. Denoising results are tabulated in Table IV. The proposed adaptive wavelet packets outperform both the full wavelet packets [3] and the fixed anisotropic wavelet packets [4] for all the test images and videos. The improvement is more significant for Barbara and Mobile than Lena and Foreman. The reason is that the room for exploiting efficient representation with adaptive wavelet packets is larger for images and videos that contain more directional features, e.g., Barbara and Mobile. For the same reason, the full wavelet packet decomposition provides better performance than the fixed anisotropic wavelet packets for Barbara and Mobile, but is inferior for Lena and Foreman.

B. Image Denoising Results

Image denoising results of our method are compared with other methods in Table V. Four other denoising schemes using complex wavelets are compared: the Oracle Shrink with a steerable complex wavelet the mixed Laplacian model with local parameters (BLMShrL) [4], the bi variate model with local variance estimation and the multivariate generalized Gaussian model (MGGD). The optimum threshold of empirically searched for each image under each noise level. The shrinkage functions are evaluated for both real wavelets and complex wavelets. Here generated Results by 2-D DDWT for comparison. For BiShrL, 0.03 dB is subtracted from the results since PSNR is defined as \(10 \log_{10} \left( \frac{256^2}{MSE} \right)\) in [4]. As shown in Table V, our method achieves better denoising performance than other DDWT-based denoising methods, e.g., BLMShrL, BiShrL, and MGGD, for Barbara that contains rich directional features. For images mainly with smooth regions such as Lena, our method does not show superiority over these methods in terms of PSNR.

In proposed method with other denoising schemes that use redundant transforms: the wavelet pair and the steerable pyramid with Gaussian scale mixture (GSM) [3]. The denoising results of GSM are generated by the software provided at [8], and those of other two schemes are taken from the published results. The proposed scheme outperforms PFrame up to 1.9dB, and shows better denoising results (0.30 dB) than W Pair. Compared with GSM, our denoising scheme gives slightly lower PSNR (0.17 dB on average). The reason may be that the dependency modeling of coefficients in GSM is more accurate by using a more redundant transform: the redundancy of steerable pyramid is 18:1 while that of 2-D ADDWP is 4:1. The increased redundancy of GSM, however, also leads to higher requirement on memory and computation. Under the same running platform, the propose method (2.82 s) is about 18 times faster than GSM (50.58 s) for denoising a noisy image. The superiority of computational complexity of the proposed method is more significant when extended to 3-D case for video denoising.

Generally speaking, denoising schemes using DDWT provide better performance than those based on real wavelet transforms. The proposed method gives better denoising results over three classic denoising methods, the hidden Markov tree model (HMT) and the locally adaptive window-based denoising using MAP (LAWMAP) [6]. The results of these methods are not shown here, and can be found in their corresponding published papers. To illustrate the visual quality, enlarged patches of clean images, noisy images, and denoised images generated by our method are shown in Fig. 6 for comparison.

| TABLE IV |
| IMAGE AND VIDEO DENOISING RESULTS OF THE PROPOSED METHODS WITH DIFFERENT WAVELET PACKET DECOMPOSITION STRUCTURES. FULL: FULL WAVELET PACKETS [3]; FIXED: THE FIXED ANISOTROPIC DECOMPOSITION STRUCTURE [4]; ADAPTIVE: THE PROPOSED ADDWP. |

<table>
<thead>
<tr>
<th></th>
<th>Barbara</th>
<th>Lena</th>
<th>Mobile</th>
<th>Foreman</th>
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<tr>
<td></td>
<td>Full</td>
<td>Fixed</td>
<td>Adaptive</td>
<td>Full</td>
</tr>
<tr>
<td>10</td>
<td>33.30</td>
<td>33.26</td>
<td>33.77</td>
<td>34.73</td>
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<td>15</td>
<td>31.38</td>
<td>31.27</td>
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<td>20</td>
<td>29.95</td>
<td>29.83</td>
<td>30.36</td>
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<tr>
<td>25</td>
<td>28.64</td>
<td>28.51</td>
<td>28.95</td>
<td>30.27</td>
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<tr>
<td>30</td>
<td>27.87</td>
<td>27.71</td>
<td>28.24</td>
<td>28.37</td>
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</table>

In images recovered by BiShrL, smooth regions around edges present dirty “clouds” due to the ringing artifacts. Our method does not have these artifacts and preserves geometry structures more faithfully. Our method also
provides visually appealing denoised results even for Lena in which our method does not show PSNR improvement. This is due to the high image representation efficiency of 2-D ADDWP, which facilitates signal and noise separation in denoising.

C. Video Denoising Results

Apply ADDWP to video denoising in two ways: one is to apply 3-D ADDWP on the whole video volume and the other is to apply 2-D ADDWP on each frame separately. The thresholding strategy is the adaptive bivariate shrinkage described in Section IV-B. For comparison, here implementing the 3-D DDWT with (3-D) BiShrL and apply the 2-D DDWT with BiShrL frame-wise for video denoising. For convenient reference 3-D ADDWP and 3-D DDWT as 3-D transforms while 2-D ADDWP and 2-D DDWT as 2-D transforms. The denoising results of these methods are shown in Table VI. It can be observed that the denoising schemes with 3-D transforms outperform those with 2-D transforms by 2 Db on average. The performance improvement is more significant for sequences with low-to-medium intensity motion, such as News, Foreman, and Tennis, and is less significant for sequences with high intensity motion such as Football. This is consistent with the observation in our previous work on video coding: the performance of frame-wise processing with 2-D DDWT is very close to that of volume-wise processing with 3-D DDWT when the motion in the sequence is beyond the capturing capability of 3-D DDWT [5]. With enhanced motion capturing capability, the 3-D ADDWP-based scheme shows significant improvement over the 3-D DDWT based scheme, which demonstrates the effectiveness of the proposed adaptive wavelet packets. The improvement of the 2-D ADDWP-based scheme over the 2-D DDWT-based scheme is not as significant as that of the 3-D ADDWP-based scheme over the 3-D DDWT-based scheme in terms of PSNR. The reason may be that the representation efficiency improvement of wavelet packet decomposition on video is more significant than that on image. The frame-wise PSNRs of denoised video produced by above methods are shown in Fig. 7 for Tennis and News. The 3-D ADDWP-based method outperforms the 3-D DDWT-based method consistently for all frames.

IV. SIMULATION RESULTS

The proposed algorithm is implemented in four domains, viz., Wavelet domain, Slantlet domain, DD DT DWT and DT-CWT domain used 256 x 256 size images and results are obtained by running the algorithm in Matlab 7.0 software. The summary of the results obtained for some of the images are given in table I. The following figure shows the comparison between four transforms in terms of PSNR values vs BPP (bits per pixel) rate. The results obtained show that DT-CWT outperforms the other transforms in terms of visual quality and embedding capacity.

![Comparison of Wavelet, Slantlet, Double Density Dual Tree Discrete Wavelet Transform, and Double Density Dual Tree Complex Wavelet Transform](image)

An improved steganographic algorithm based on the modified LSB technique using four different transforms, viz., DWT, SLT, DD DT DWT and DT-CWT is presented and compared in terms of visual quality and embedding capacity. The modified LSB method can be implemented conveniently and for high capacity data can be embedded using two or more LSBs bits per pixel. The disadvantage of the LSB method is that it is non-robust. Cleik et al. [19] have proposed Generalized-LSB data embedding that offers finer grain scalability along the capacity distortion curve. The purpose of this paper was to investigate complex wavelet transforms as an application to steganography and compare it with already known transform domains such as classical Haar or standard discrete wavelets and Wavelet-like transforms. The authors have also applied other techniques such as Thresholding technique and Wavelet-fusion technique [20]. Through experimental results they have observed that DT-CWT domain is superior than DWT or SLT domain in view of visual quality of stego-image and embedding capacity. Thompson et al. [21] have shown that DT-CWT domain is good robustness against several attacks such as Wiener filtering, Median filtering, Mean filtering, JPEG compression, and AWGN attacks for image watermarking based on Spread Spectrum and Quantization Index Modulation. Here finding a secure high capacity steganographic algorithm in the DT-CWT domain that is robust to common attacks such as low-pass filtering, JPEG compression and Gaussian noise.
VI. REFERENCES


