

# BLIND VIDEO DATA HIDING USING INTEGER WAVELET TRANSFORMS

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## ABSTRACT

A proposed blind video data hiding approach, for embedding different types of data in video frames is presented. Video signal is a highly correlated signal, this correlation is stemming from two sources. The first one is the spatial correlation that results from inter-pixel correlation within each frame of the video sequence. The second one is the temporal correlation that results from the slow time varying nature of the video signals. In this paper integer wavelet transforms are used to exploit the spatial and temporal correlation in and between the video frames for minimizing the embedding distortion. The proposed work achieves zero bit error rate (BER) between the original and the recovered data. Using the one dimensional integer wavelet transform across the temporal axis gives superior results with a margin approximately above 2 dB in the sense of PSNR (Peak Signal to Noise Ratio) in comparison of using the two and three dimensional integer wavelet transforms. However, the one dimensional integer wavelet transform has the lowest computational costs.

## KEYWORDS

Blind Data Hiding – Video Data Hiding – Integer Wavelet Transform – Temporal Correlation - HVS.

## 1- INTRODUCTION

Ever improving network bandwidths, computer speeds, digital storage capacities, and wireless capabilities, are changing our lives right from the way we entertain ourselves, communicate with each other, or assimilate and disseminate knowledge, to the way we operate our bank accounts. A key driver for these changes has been the rapid growth in the demand and consumption of digital multimedia content. This has, however, lead to some valid concerns over multimedia content security, authenticity, and intellectual property rights.

Multimedia data hiding, defined as imperceptible embedding of information into a multimedia host, provides potential solutions, though with many unseen challenges. Because of its potential applications in multimedia content security, data hiding continues to receive considerable attention from the research community. Multimedia data hiding offers unique challenges that require integration of various disciplines, such as image processing, computer vision, information theory, signal compression, error correction coding, and communication theory [1].

Data hiding techniques are categorized as non-blind or blind techniques. In *non-blind* data hiding systems, it is assumed that the original host or cover is available at the decoder. In this case, the problem

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reduces to the classical communications (or data transmission) problem, in which a message has to be transmitted to the receiver in the presence of *noise*. For *blind* information hiding systems, the decoder does not have an access to the original cover signal. However, viewing the cover signal as noise disregards the fact that it is actually known to the encoder, who can use this extra information to its advantage. By considering the knowledge of the host signal at the encoder, the data hiding problem can be modeled as communications process with *side information* about the channel-state at the encoder [2].

Several techniques for blind hiding of the information in images have been presented in the literature. Most of these are intended for watermarking, where the main requirement is a high robustness to ensure survivability even in the presence of intentional removal attacks; in such a scenario, the perceptibility of the embedded message is of no concern as long as it does not degrade the quality of the cover beyond a certain degree. Also, in watermarking the required amount of embedded data is low; indeed as little as one bit may be sufficient (to confirm ownership or otherwise).

On the other hand, comparatively much less work has been done in the related field of steganography where the objective is to hide as much data as possible within the cover; this can be used in applications as diverse as covert data transfer, in-band captioning, and image augmentation. In this scenario, bandwidth efficiency plays a vital role; imperceptibility is also a requirement, at varying degrees depending on the application. In covert communications, for instance, the process should leave the cover statistically similar to typical images in all possible ways. In other applications it may be sufficient to keep the process perceptually invisible. It is clear that with so much diversity in their requirements, the design problem is quite different for information hiding techniques intended for steganography as compared to watermarking.

Most high-capacity techniques in the literature are based on the least-significant-bit (LSB) hiding techniques. A natural way to embed information into a media host without inducing any perceptual distortion is to modify the least significant bit of the media samples. The LSB hiding is one of the first methods proposed for data embedding [3]. This scheme has been applied for both the classical applications of data hiding: digital watermarking [4] and covert communication [5].

Spread-spectrum (SS) hiding was introduced by Cox et al [6] to alleviate the problems of LSB hiding against attacks. The method, derived from its communications counterpart, involves adding a spread sequence to the image. The spread sequence is constructed from the message to be hidden. The method and its variations (e.g., [7, 8]), proposed for watermarking applications, are robust against many attacks such as compression, noise addition, and signal processing operations. Spread-spectrum hiding has been used for steganography [9] as well. However, in general, it is well-known that the embedding capacity of SS techniques is quite low, especially for blind implementations.

The Patchwork method takes advantage of the fact that the human eye cannot easily detect varying amounts of light [10]. The Patchwork method gets its name by “using redundant pattern encoding to repeatedly scatter hidden information throughout the cover image, like patchwork” [11].

Using a phase-coding approach, data are embedded by modifying the phase values of Fourier transform coefficients of cover segments ([12] and [13]).

Data can be embedded into the multimedia content in spatial domain or in frequency domain. Frequency domain watermarking methods may use several different domains, such as discrete cosine transformation (DCT) domain, discrete Fourier transformation (DFT) domain, discrete wavelet transformation (DWT) domain, etc. In the literature, it is pointed that the frequency domain techniques are more robust than spatial domain techniques [14].

Because video data can be represented as multiple two-dimensional images, it is possible to code these two-dimensional frames independently on an image by image basis. Most the techniques in the literature that deal with the video data hiding apply the same still image data hiding techniques ([15], [16 ], [17 ] ) . However, such two dimensional methods do not exploit the dependencies that exist among pixel values in all three dimensions, a better approach is to consider the whole video frames as a single three-dimensional data set.

In this paper integer wavelet transforms are used to exploit the spatial and temporal correlation between the video frames to minimize the embedding distortion depending on the type of the transform (1-D, 2-D, or 3-D). The proposed work achieves zero bit error rate (BER) between the original and the recovered data which makes the proposed work capable of embedding text, images, or speech data in the video frames.

This work reveals the power of different integer wavelet transforms and compares between them through exhaustive experiments to choose the best one in the sense of minimizing the distortion metric. Also, the study determines the sensitivity of the different types of video frames to the embedding distortion. The paper is organized as follows: section 2 introduces the integer wavelets used in the proposed work. The proposed work is presented in section 3. The results and experiments are presented in section 4. Finally, section 5 summarizes the conclusions, and proposed future investigations.

## 2- INTEGER WAVELET TRANSFORMS

The wavelet transform is a valuable tool for Multiresolution analysis that has been widely used in image processing applications. The wavelet transform has a number of advantages over other transforms as it provides a multiresolution description, it allows superior modeling of the human visual system (HVS), the high-resolution sub bands allow easy detection of features such as edges or textured areas in transform domain. In the transform coding of images, the image is projected onto a set of basis functions, and the resultant transform coefficients are encoded. Efficient coding requires that the transform compact the energy into a small number of coefficients.

### 2.1-ONE DIMENSIONAL DISCRETE WAVELET TRANSFORMS

A general 1-D discrete wavelet transform can be written as [18]:

$$W(j,k) = \frac{1}{\sqrt{M}} \sum_x f(x) 2^{j/2} \psi(2^j x - k) \quad (1)$$

$$\psi(x) = \begin{cases} 1 & 0 \leq x < 0.5 \\ -1 & 0.5 \leq x < 1 \\ 0 & \text{elsewhere.} \end{cases} \quad (2)$$

where W represents the wavelet coefficients function, j , k denote the dilation and translation parameters respectively, and M is the length of the sequence f.

### 2.2-Two Dimensional Discrete Wavelet Transform

The one-dimensional wavelet transform can easily extended to two-dimensional functions like images. In two dimensions, a two-dimensional scaling function,  $\phi(x,y)$ , and three dimensional wavelets,

$\psi^H(x, y), \psi^V(x, y), \psi^D(x, y)$ , are required. Each is the product of a one-dimensional scaling function  $\phi$  and corresponding wavelet  $\psi$ . Excluding products that produce one-dimensional results, like  $\phi(x)\psi(x)$ , the four remaining products produce the separable scaling function:

$$\phi(x, y) = \phi(x)\phi(y) \quad (3)$$

and separable, "directionally sensitive" wavelets :

$$\psi^H(x, y) = \psi(x)\phi(y) \quad (4)$$

$$\psi^V(x, y) = \phi(x)\psi(y) \quad (5)$$

$$\psi^D(x, y) = \psi(x)\psi(y) \quad (6)$$

Given separable two-dimensional scaling and wavelet functions, extension of the one-dimensional DWT to two dimensions is straightforward. The scaled and translated basis functions are:

$$\phi_{j,m,n}(x, y) = 2^{j/2} \phi(2^j x - m, 2^j y - n) \quad (7)$$

$$\psi^i_{j,m,n}(x, y) = 2^{j/2} \psi(2^j x - m, 2^j y - n), \quad i = \{H, V, D\} \quad (8)$$

where index  $i$  identifies the directional wavelets in Eqn.(4) to (6). The discrete wavelet transform of function  $f(x, y)$  of size  $M \times N$  is then :

$$W_\phi(j_0, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \phi_{j_0, m, n}(x, y) \quad (9)$$

$$W_\psi^i(j, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \psi^i_{j, m, n}(x, y) \quad i = \{H, V, D\} \quad (10)$$

As in the one-dimensional case,  $j_0$  is an arbitrary starting scale and the  $W_\phi(j_0, m, n)$  coefficients define an approximation of  $f(x, y)$  at scale  $j_0$ . The  $W_\psi^i(j, m, n)$  coefficients add horizontal, vertical, and diagonal details for scales  $j \geq j_0$ . Given the  $W_\phi$  and  $W_\psi^i$  of Eqn. (9) and (10),  $f(x, y)$  is obtained via the inverse discrete wavelet transform:

$$f(x, y) = \frac{1}{\sqrt{MN}} \sum_m \sum_n W_\phi(j_0, m, n) \phi_{j_0, m, n}(x, y) + \frac{1}{\sqrt{MN}} \sum_{i=H, V, D} \sum_{j=j_0}^{\infty} \sum_m \sum_n W_\psi^i(j, m, n) \psi^i_{j, m, n}(x, y) \quad (11)$$

### 2.3-THREE DIMENSIONAL DISCRETE WAVELET TRANSFORM

In three dimensions, a three-dimensional scaling function,  $\phi(x, y, z)$  and seven three-dimensional wavelet  $\psi^{LLH}(x, y, z), \psi^{LHL}(x, y, z), \psi^{LHH}(x, y, z), \psi^{HLL}(x, y, z), \psi^{HLH}(x, y, z), \psi^{HHL}(x, y, z), \psi^{HHH}(x, y, z)$

,are required. Each is the product of a one-dimensional scaling function  $\phi$  and corresponding wavelet  $\psi$ . Excluding products that produce one-dimensional results, like  $\phi(x, y, z)\psi(x, y, z)$ , the eight remaining products produce the separable scaling function:

$$\phi(x, y, z) = \phi(x)\phi(y)\phi(z) \quad (12)$$

and separable, "directionally sensitive" wavelets :

$$\psi^{LLH}(x, y, z) = \phi(x)\phi(y)\psi(z) \quad (13)$$

$$\psi^{LHL}(x, y, z) = \phi(x)\psi(y)\phi(z) \quad (14)$$

$$\psi^{LHH}(x, y, z) = \phi(x)\psi(y)\psi(z) \quad (15)$$

$$\psi^{HLL}(x, y, z) = \psi(x)\phi(y)\phi(z) \quad (16)$$

$$\psi^{HLH}(x, y, z) = \psi(x)\phi(y)\psi(z) \quad (17)$$

$$\psi^{HHL}(x, y, z) = \psi(x)\psi(y)\phi(z) \quad (18)$$

$$\psi^{HHH}(x, y, z) = \psi(x)\psi(y)\psi(z) \quad (19)$$

Given separable three-dimensional scaling and wavelet functions, extension of the one-dimensional DWT to three dimensions is straightforward. The scaled and translated basis functions are:

$$\phi_{j,m,n,o}(x, y, z) = 2^{j/2}\phi(2^j x - m, 2^j y - n, 2^j z - o) \quad (20)$$

$$\psi^i_{j,m,n,o}(x, y, z) = 2^{j/2}\psi(2^j x - m, 2^j y - n, 2^j z - o), \quad i = \{LLH, LHL, LHH, HLL, HLH, HHL, HHH\} \quad (21)$$

where index  $i$  identifies the directional wavelets in Eqn.(13) to (19). The discrete wavelet transform of function  $f(x,y,z)$  of size  $M \times N \times O$  is then :

$$W_\phi(j_0, m, n, o) = \frac{1}{\sqrt{MNO}} \sum_{z=0}^{O-1} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y, z)\phi_{j_0,m,n,o}(x, y, z) \quad (22)$$

$$W_\psi^i(j, m, n, o) = \frac{1}{\sqrt{MNO}} \sum_{z=0}^{O-1} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y, z)\psi^i_{j,m,n,o}(x, y, z), \quad i = \{LLH, LHL, LHH, HLL, HLH, HHL, HHH\} \quad (23)$$

As in the one-dimensional case,  $j_0$  is an arbitrary starting scale and the  $W_\phi(j_0, m, n, o)$  coefficients define an approximation of  $f(x,y,z)$  at scale  $j_0$ . The  $W_\psi^i(j, m, n, o)$  coefficients add horizontal, vertical, and diagonal details for scales  $j \geq j_0$ . Given the  $W_\phi$  and  $W_\psi^i$  of Eqn. (22) and (23),  $f(x, y, z)$  is obtained via the inverse discrete wavelet transform:

$$f(x, y, z) = \frac{1}{\sqrt{MNO}} \sum_o \sum_m \sum_n W_\phi(j_0, m, n, o)\phi_{j_0,m,n,o}(x, y, z) + \frac{1}{\sqrt{MNO}} \sum_{i=LLH}^{HHH} \sum_{j=j_0}^{\infty} \sum_o \sum_m \sum_n W_\psi^i(j, m, n, o)\psi^i_{j,m,n,o}(x, y, z) \quad (24)$$

It is proved theoretically that wavelet transform can be implemented by use of perfect reconstruction finite impulse response filter banks [19]. The analysis filter bank decomposes the input signal  $f(x)$  into two subband signals,  $L(n)$  and  $H(n)$ . The signal  $L$  represents the low frequency part of  $f(x)$ , while the signal  $H$  represents the high frequency part of  $f(x)$ . The analysis filter bank convolves  $f(x)$  with a lowpass filter  $h_0$  and a highpass filter  $h_1$  then down sample the resultant signals as shown Fig.(1) .

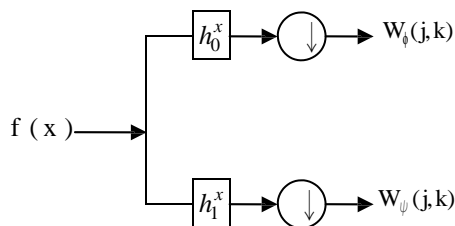


Fig. (1): 1-D wavelet analysis filter bank.

To use the wavelet transform for image processing a 2D version of the filter bank is used. In the 2D case, the 1D analysis filter bank is first applied to the columns of the image and then applied to the rows. If the image has  $M$  rows and  $N$  columns, then after applying the 1D analysis filter bank to each column there exists two subband images, each having  $\frac{M}{2}$  rows and  $N$  columns. After applying the 1D analysis filter bank to each row of both of the two subband images, this results in four subband images, each having  $\frac{M}{2}$  rows and  $\frac{N}{2}$  columns. This is illustrated in Fig. (2).

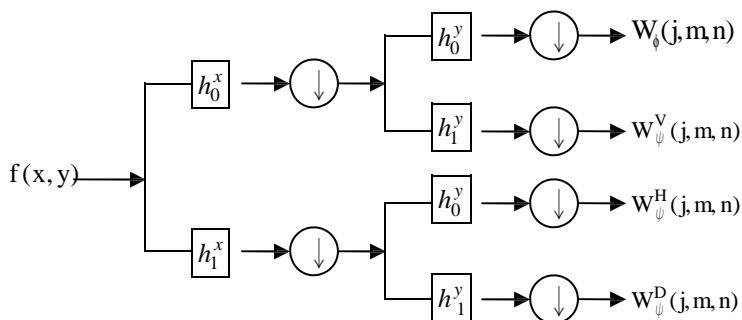


Fig. (2): One stage in multi-resolution wavelet decomposition of an image.

To extend the wavelet transform for using in volume and video processing we must implement a 3D version of the filter banks. In the 3D case, the 1D analysis filter bank is applied in turn to each of the three dimensions. If the data is of size  $M$  by  $N$  by  $F$ , then after applying the 1D analysis filter bank to the first dimension we have two subband data sets, each of size  $\frac{M}{2} \times N \times F$ . After applying the 1D analysis filter bank to the second dimension we have four subband data sets, each of size  $\frac{M}{2} \times \frac{N}{2} \times F$ . Applying the 1D

analysis filter bank to the third dimension gives eight subband data sets, each of size  $\frac{M}{2} \times \frac{N}{2} \times \frac{F}{2}$ . The block diagram of the 3D analysis filter bank is shown in Fig. (3).

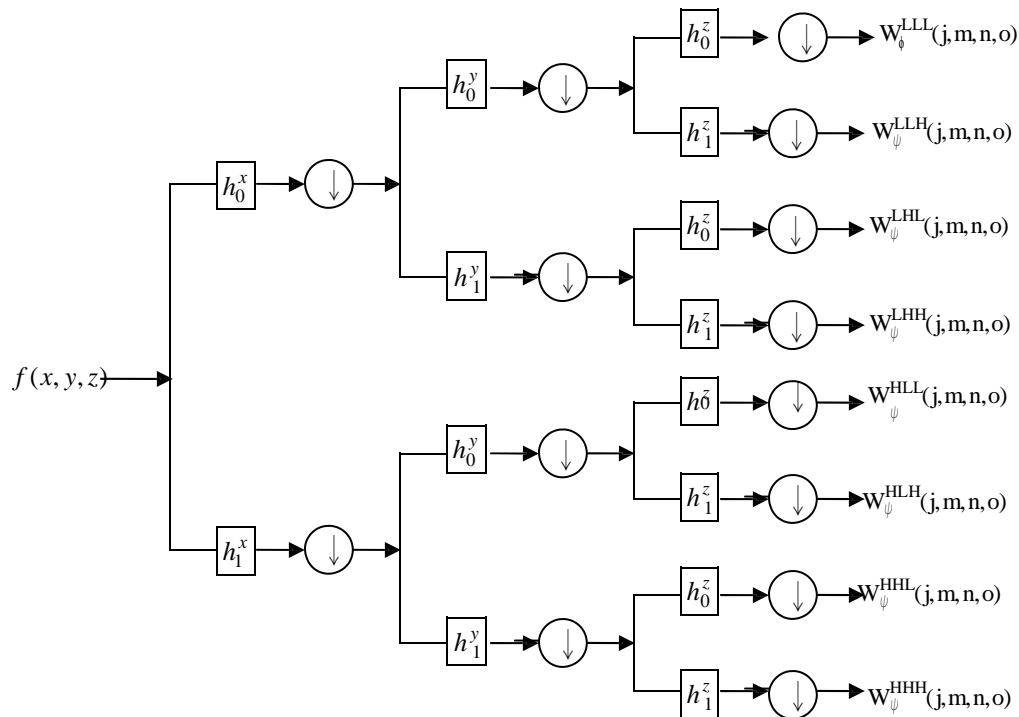


Fig. (3): Block diagram of a single level decomposition for the 3D DWT.

#### 2.4-S -TRANSFORM

The wavelet transform, in general, produces floating point coefficients. Although these coefficients can be used to reconstruct the original signal perfectly in theory, the use of finite precision arithmetic and quantization results in a lossy scheme. Recently, reversible integer wavelet transforms, i.e., wavelet transforms that transform integers to integers and allow perfect reconstruction of the original signal, have been introduced. One can create integer wavelet transforms by using the lifting scheme by rounding-off the result of each dual-lifting and lifting step before adding or subtracting. S-transform [20] is used to implement the integer wavelet transforms its smooth  $s$  and detail  $d$  outputs for an index  $n$  are given as following:

$$s(n) = \left\lfloor \frac{x(2n) + x(2n+1)}{2} \right\rfloor \quad (25)$$

$$d(n) = x(2n) - x(2n+1) \quad (26)$$

Note that the smooth and detail outputs are the results of applying the lowpass and highpass filters respectively. The synthesis filters are:

$$x(2n) = s(n) + \left\lfloor \frac{d(n)+1}{2} \right\rfloor \quad (27)$$

$$x(2n + 1) = s(n) - \left\lfloor \frac{d(n)}{2} \right\rfloor \quad (28)$$

In conjunction with the before mentioned filter banks the 1D, 2D, and 3D integer wavelet transform can be realized in efficient way using the S-transform.

### 3- THE PROPOSED SYSTEM

The proposed system start working by decomposing each frame of the cover video sequence into red, green, and blue frames, then cascading them across the whole video sequence which generates three new cover video sequences which resemble the red, green, and blue frames. Then for each video sequence the discrete integer wavelet transform (DIWT) is performed and the secret data is embedded using the least significant bit technique (LSB) in this transform domain, lastly, the inverse discrete integer wavelet transform (IDIWT) is applied. Finally, all the three processed sequences are merged to form the stego video sequence. Fig. (4) depicts the system block diagram. The message encoding stage encodes the secret data (text data, image, or even video sequence) into a stream of zeros and ones (binary data). According to the type of the integer wavelet transform, the effect of diffusing the secret data across the whole cover video sequence and consequently the distortion due to embedding is inherently attenuated or amplified.

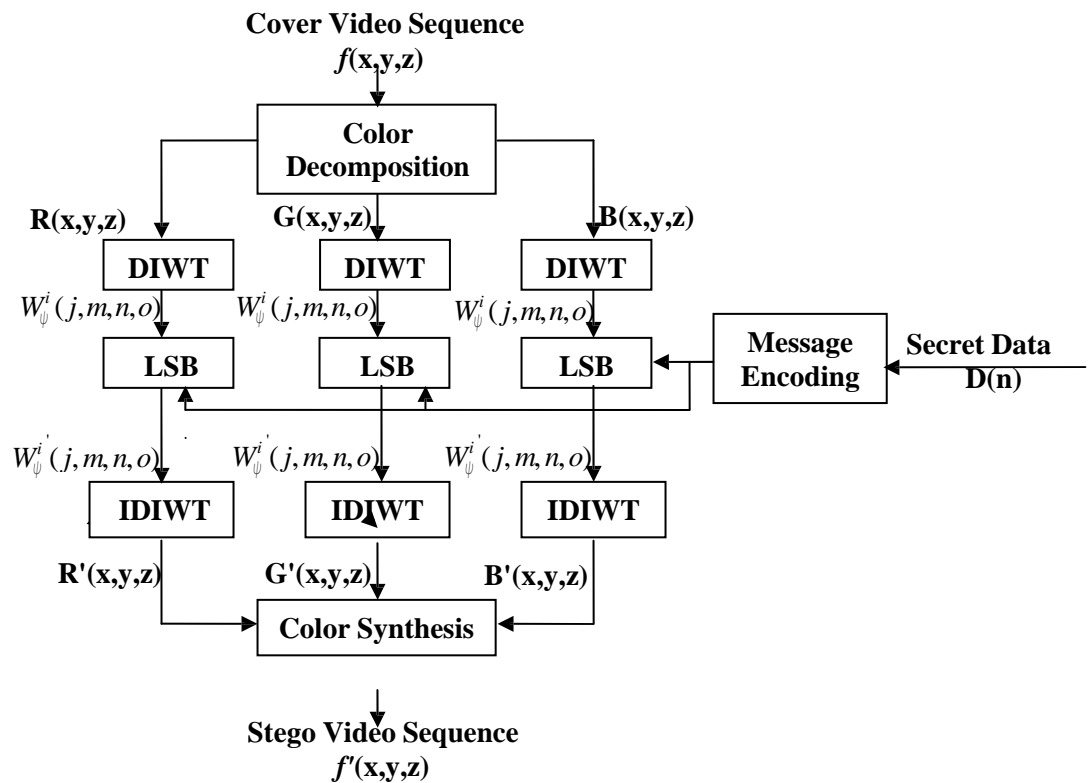


Fig.(4): The proposed video data hiding system block diagram.

Video signal is a highly correlated signal, this correlation is stemming from two sources. The first one is the spatial correlation that results from the inter-pixel correlation within each frame of the video sequence. The second one is the temporal correlation that results from the slow time varying nature of the video signals. Fig. (5) shows four consecutive frames that belong to the same video sequence, it is apparent that there exists a high correlation due to frame-to-frame relationships that exists across the time.



Fig. (5): Four Consecutives frames of the same video showing the dependencies among the video frames.

Since the video sequences contains a large amount of redundancies due to spatial and temporal correlation, one way to hide the secret data into the video sequence is to de-correlate the video sequence to reserve a free space to utilize it in the hiding process. The proposed work uses the integer wavelet transform to de-correlate the video signals due to its success in modeling the human visual system (HVS) and a large spectrum of signals like speech and images. If 2D-DIWT is used, the temporal correlation effect is lost, because each frame of the video sequence is processed individually. In other words 2D-DIWT captures only the spatial correlation that exists in each frame as Fig. (6) shows.

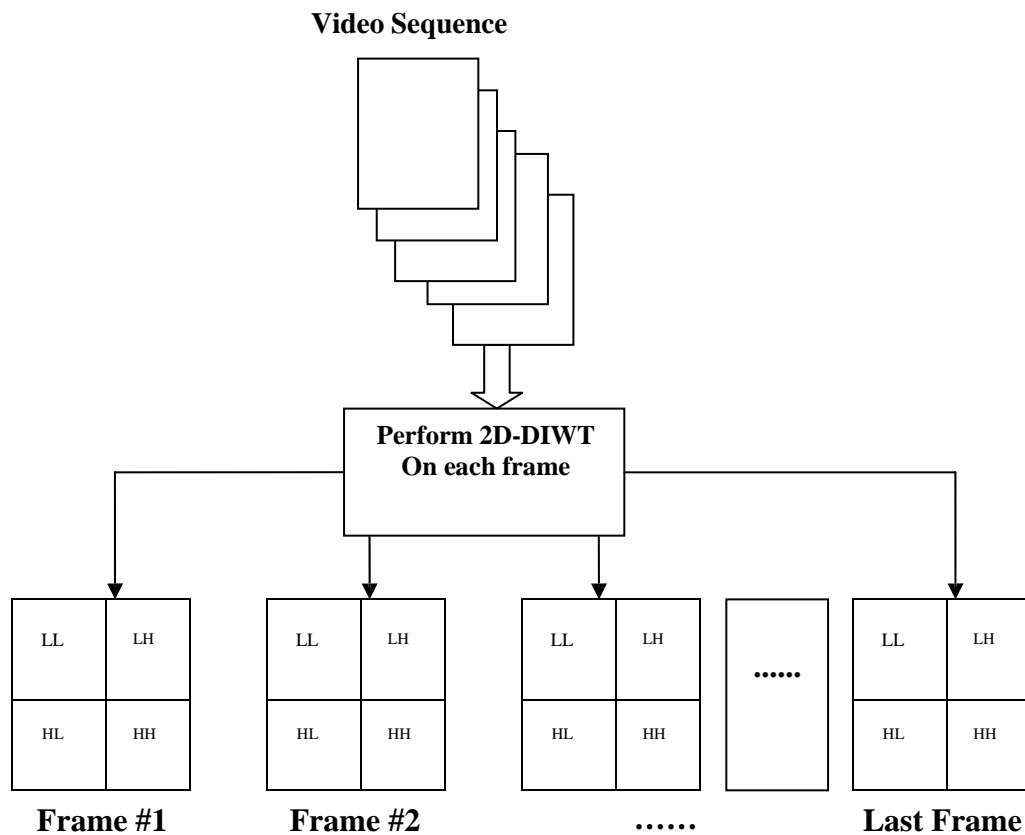


Fig.(6): 2-D wavelet transform decomposition for video frames.

3D-DIWT captures both types of correlation in the video sequence as it works by applying 2D-DIWT across each frame, then cascade them, and finally perform 1D-DWT along the time axis of each pixel in the video sequence, Fig.(7) depicts this operation.

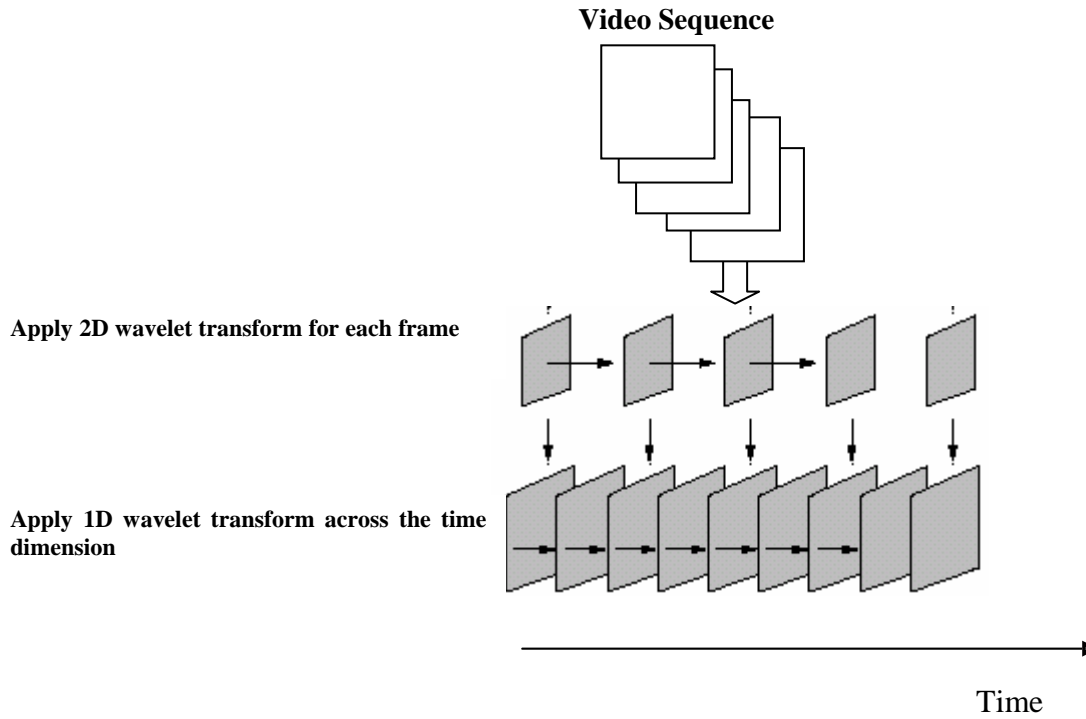


Fig.(7): 3-D wavelet transform for video signal.

If the stage of 2D-DIWT is omitted when performing 3D-DIWT the resultant is a stage performs the 1D-DIWT across the time axis as Fig.(8) shows. So there exist three different configuration of DIWT.

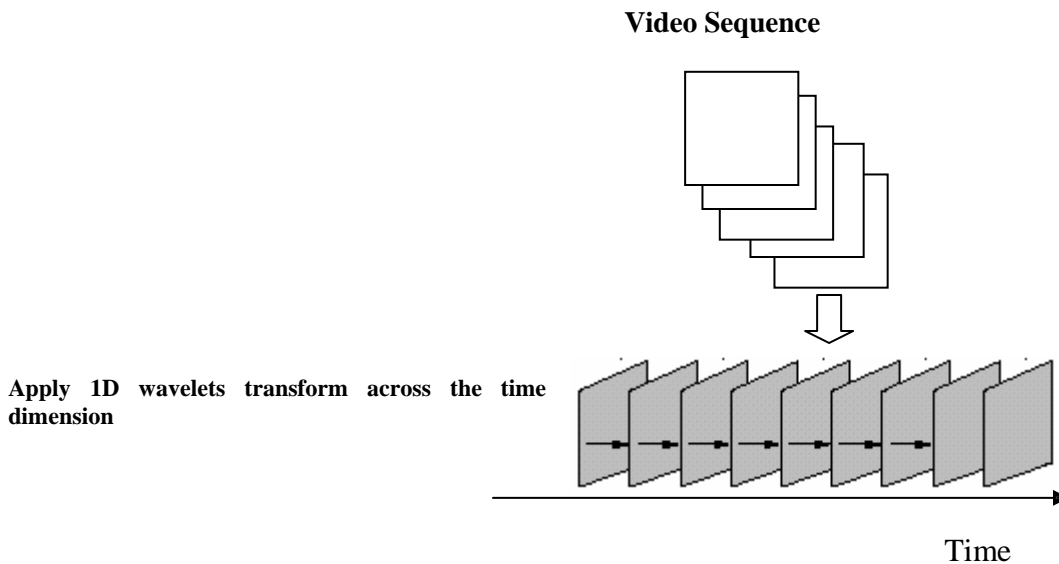


Fig.(8): Temporal 1-D wavelet transform decomposition for video frames

#### 4- EXPERIMENTAL RESULTS AND DISCUSSIONS

A database of 32 color video sequences is used to conduct the experiments. Each video sequence has 512 color frames, thus each video has 1536 frames. Each frame has a size of 256 \*256 pixels. The video collection contains a large variety of video patterns like fine details, textures, and edges. In all the experiments peak-to-signal noise ratio (PSNR) is used as a comparison metric.

$$PSNR = \frac{20}{NF} \sum_{k=1}^O \log_{10} \left( \frac{255}{\sqrt{\frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N \left( X(i, j, k) - \bar{X}(i, j, k) \right)^2}} \right) \quad (29)$$

where

- X and  $\bar{X}$  are the cover and stego video sequences
- M and N are the width and the height of each video frame in pixels
- O is the number of the frames in the video sequence

The first type of experiments aims to investigate the performance of the proposed system using integer wavelet transforms against LSB technique and also among the different integer wavelet transform with each others. So, a text data of different length is encoded into binary streams, then the encoded data is embedded into the video sequences of the data base using different configurations.

It is clear from Fig.(9) that temporal 1-D DIWT is superior to LSB, 2D-DIWT and 3D-DIWT. The main reason behind this is: the quantization effect due to using integer wavelets which smear out the gain of convolving across the time axis using wavelets. So performing 1D-DIWT directly on the cover video sequence in the spatial domain across the time axis will (as the figure explains) give the best results. This important results emphasis the success of dealing with the video signal as three dimensional signal in data hiding thus capturing the dependencies exists among the consecutive frames. Also this result reveals that the superiority performance of the 1-D DIWT against 3-D DIWT although the later highly computable with regards to the former.

The last set of experiments tried to explore the sensitivity of red, green, and blue frames due to the distortion that results from the hiding process. To this end, the before mentioned experiments are repeated, with one exception that is instead of measuring the average PSNR across the whole sequence, this metric is divided to three metrics which correspond to red, green, and blue frames. Fig.(10), Fig.(11), and Fig.(12) indicate that the most regular channels is the blue channel. This result coincides with the other works about the image hiding in the spatial and frequency domains [21]. And in the same time coincides with the sensitivity of the human visual system that has a least sensitivity with the blue colors [18]. So, the blue frames can accept more hiding capacity than the red and green frames at the same value of the distortion metric like PSNR. Consequently, the priority is to blue frames when spreading the encoded data across the video sequences.

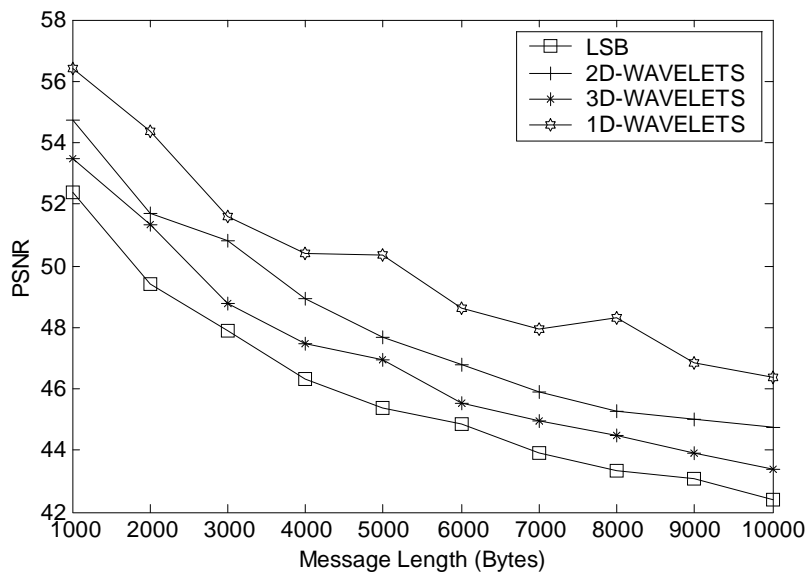


Fig.(9): The performance of the proposed systems against LSB technique for video data hiding

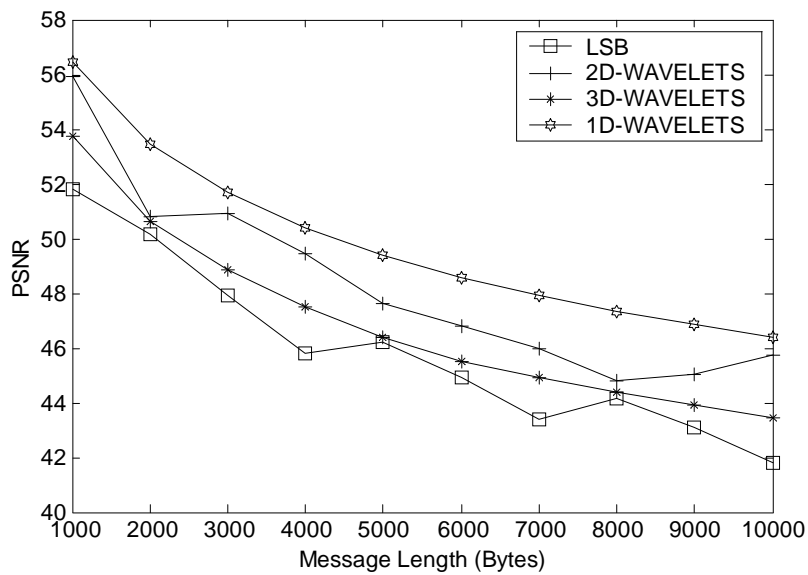


Fig.(10): The performance of the proposed systems against LSB for video data hiding in red frames

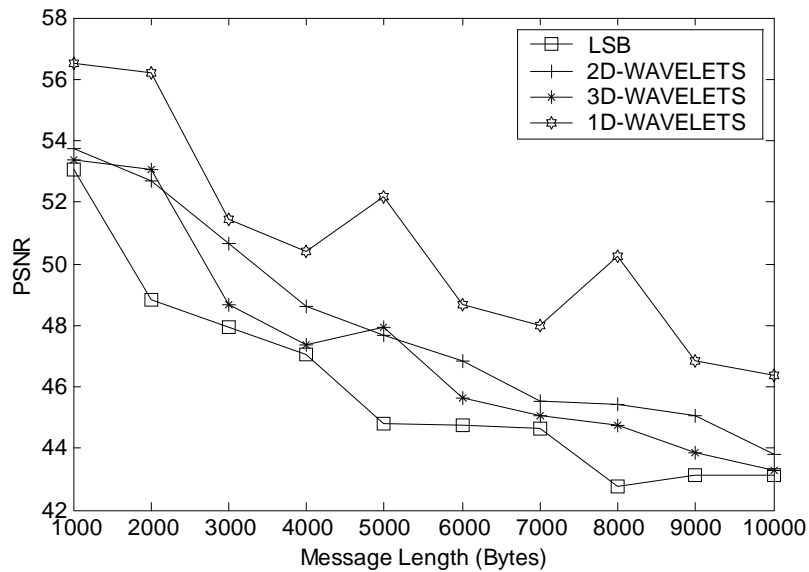


Fig.(11): The performance of the proposed systems against LSB for video data hiding in green frames

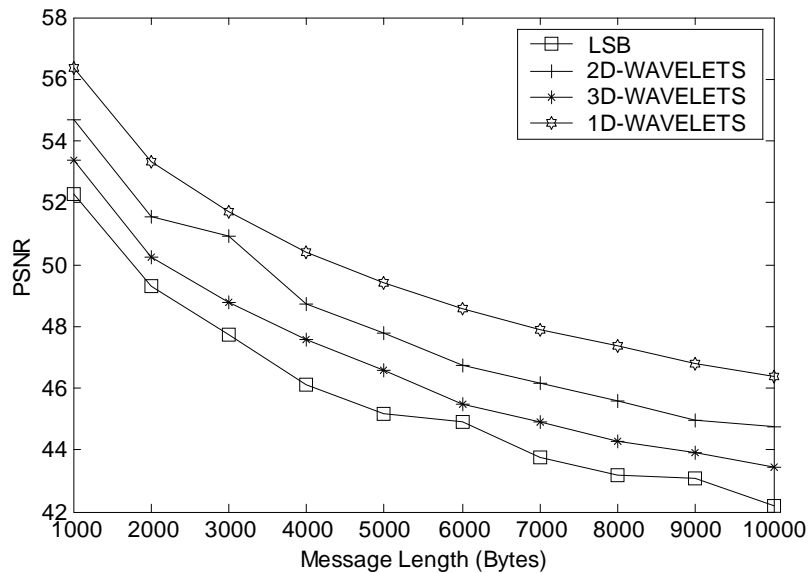


Fig.(12): The performance of the proposed systems against LSB for video data hiding in blue frames

## 5- CONCLUSIONS

In this paper a blind video data hiding is proposed. The experiments emphasize the success of dealing with the video signal as three dimensional signal in data hiding thus capturing the dependencies among the consecutive frames(temporal correlation) rather than directly applying the still images data hiding techniques that deal with the video frames independently ( spatial correlation ). Using the one dimensional integer wavelet transform across the video time axis gives superior results against using two and three dimensional integer wavelet transforms, consequently the video signal that contains an audio stream beside the frames stream can use the same data hiding architecture without introducing a new

overhead. The experiments show that the blue frames has a least sensitivity with respect to the embedding distortion. Hence, the priority is to blue frames when spreading the encoded data across the video sequences.

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