

Nature Inspired Algorithm for Pixel Location Optimization in Video Steganography Using Deep RNN

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Abstract: The steganography is applied on text, image, video, and audio files. The steganography is useful for safe and secure data transmission. Video steganography is used to preserve confidential information of security applications. To improve security of the message, pixels locations are optimized using nature inspired algorithm. As conventional algorithms have a low convergence rate a new algorithm is proposed. A New algorithm is developed by combining two model algorithms namely, Water wave optimization (WVO) and Earth worm optimization (EWO) and is renamed as proposed Water-Earth Worm Optimization (WEWO) algorithm. The frames are preprocessed and extracted using Discrete Cosine transform (DCT) and Structured Similarity index (SSIM), respectively, as regular processing. For pixel prediction, the fitness function is obtained from neighborhood entropies in proposed algorithm. In this method, secret message is embedded with two level decomposition of Wavelet Transform (WT). In the proposed work is tested with 'CAVIAR' dataset. The Proposed WEWO-Deep RNN algorithm performance is tested with modular noises such as, pepper, salt and pepper noises. The proposed method gives enhanced performance, which is seen with the parameters, Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), and Correlation Coefficient (CC) which defines image quality indices.

Keywords: Video steganography, Discrete cosine transform, Deep recurrent neural network, Wavelet transform

Introduction

The Steganography is a technique for initiating security in communication. Hiding of data in digital multimedia like audio, image, video, and text plays significant role (*Xinyu Weng et al. 2019*). Video is an amalgamation of stand still images with an audio, which changes in specified sequence of time. Video steganography is a process of concealing secret messages in bit streams of a video. The video steganography applied to various application areas like law enforcement, medical systems, access control and copyright protection etc. The embedding techniques based on video steganography comprises spatial and transform domain techniques. Least Significant Bit (LSB) substitution, Most Significant Bit (MSB) substitution, combination of LSB and MSB substitution, histogram manipulation, Region of Interest (ROI), mapping rule and matrix encoding, Pixel Value Differencing (PVD), are spatial domain techniques, (*Wang Xiang-yang et al. 2013*). When the steganography is based on transform domain, every single video image is individually converted into frequency domain by considering any of the transforms: Discrete Cosine Transform (DCT), Discrete Wavelet Transforms (DWT), and many more. A video key image is splitted into four sub-bands that help to divide odd and even coefficients utilizing different wavelet transforms. The secret message is then hid into coefficients. These approaches have increased hiding capacity, but the clarity of video gets compromised after embedding, (*Rajni et al. 2016*). To embed the maximum secret data bits within pixels of a key image, bits per pixel (BPP) is used to measure the hiding capacity of the technique, (*Shumeet Baluja 2017*). A bit substitution improves the hiding capacity of the key image without reducing the quality of the embedded image and minimum loss, (*Ramadhan Mstafaet al. 2017*). By adopting machine learning techniques and artificial intelligence algorithms, limitations of conventional steganography techniques can be avoided. Fuzzy logic based algorithms, Particle Swarm Optimization (PSO), Genetic algorithms (GA), and Neural Networks (NN), are popular approaches used to improve the imperceptibility and payload capacity, (*Yunxia Liuet al. 2019*).

In this paper, we used nature inspired algorithms (*Yu-Jun Zheng 2015*) (*Gai-Ge Wang 2018*) for the selection of the optimal pixel location within the key images for concealing the secret image bits. The proposed WEWO algorithm is employed for training Deep RNN to predict optimal pixel location. The secret message is embed with wavelet transform. The paper is organized as, next section is presenting literature review of the video steganography. Then the outline of the proposed methodology is discussed. The implementation and results are described after outline of proposed methodology. Finally, conclusion is discussed.

Literature Review

The illustration of conventional video steganography and steganalysis methods is depicted along with their limitations. (Xinyu Weng et al. 2019) developed a technique for video steganalysis and the basic contribution is two-fold method. One phase is devised for concealing inter-frame difference in the frame and another is to conceal the secret frame. The thresholding technique was adapted for determining secret video frame. (Ke. Niu et al. 2019) devised a hybrid steganographic model on the basis of game theory. The enhanced distortion function is employed for generating the bias function using game theory model. The method provides improved security and the rate of detection error was considerably enhanced. (Ramadhan Mstafa et al. 2017) proposed secure video steganographic algorithm, namely Multiple Object Tracking (MOT) algorithm using DCT and DWT with Error Correcting Codes (ECC). The secret message is pre-processed by adapting Bose, Chaudhuri, Hocquenghem (BCH) codes and used Hamming codes to encode secret data. Here, the MOT algorithm is adapted for distinguishing the interesting regions in moving objects. The data hiding is carried out by DWT and DCT coefficients. The method enhanced the security over the attacks (K. Jayasakthi Velmurugan et al. 2019) devised a method for video steganography using huge video data. The method implemented to rise security by integrating hash function and hybrid NN to determine the best bits from the video to entrench the secret message. (S. Manisha et al. 2019) developed a method for hiding and extracting the secret data in the videos. The secret message is hidden after video / image segmentation. The method offered a two-level encryption. (Mritha Ramalingam et al. 2016) proposed a data-hiding method with scene-change detection for performing steganalysis using set of videos. The reduction of distortions in the videos and safeguarding the underlying data remained as a preceding aim in video steganographic model. The method used DCT and DWT to increase the security of hidden data and reduce distortion, resulting in better video quality. The video steganography technique provides a balance between the performance of high embedding capacity, visual quality and high robustness. The technique, however, was unable to deal with unforeseen attacks. Artificial intelligence combined with video steganography algorithms delivers effective secret security and visual quality, (Yunxia Liuet al. 2019).

Aimed at the shortcomings of imperceptibility and robustness found in the video steganography we have proposed Water Earth Worm Optimization (WEWO) algorithm with Deep-RNN. It is discussed in the next part of the paper.

Proposed WEWO-Deep RNN for Video Steganography

The videos are useful media for data sharing, recordings, and communication. The videos are utilized for hiding data as they offer additional storage as compared to image. The deep learning methods are an effective approach for video steganography and provide the ability to learn without being programmed. In this paper, a DEEP RNN, (Masaya Inoue et al 2018), is employed for video steganography wherein the pixel prediction is done by training the DEEP RNN by the proposed WEWO algorithm. WWO, (Yu-Jun Zheng 2015) and EWO, (Gai-Ge Wang 2018) are combined to create the proposed WEWO. The wavelet transform is used to encrypt the secret message. As a result, the proposed WEWO- DEEP RNN method is used to forecast pixels. Implementation of methodology is carried out using following steps,

Step 1. Initially, the input video is undergo through the key frame extraction phase. The Discrete Cosine Transform and Structural Similarity Index used for key frames selection.

Step 2. The neighborhood features are extracted from key frames then these extracted features are used to WEWO-DEEP RNN-based pixel prediction model.

Step 3. The DEEP RNN is trained using the proposed WEWO algorithm, it is used to determine the pixels to be embedded.

Step 4. After that, WT is used to insert secret message. The hidden data is retrieved using wavelet-based extraction to provide the final extracted image.

Extraction of Key Frames from Videos

The Structural Similarity Index (SSIM) is a method for calculating the degree of similarity between two frames. The extraction of frames is an imperative step to split the video into the constituent frames. The keyframes are extracted using DCT and SSIM. After the application of DCT, the similarity between the two consecutive frames is evaluated using SSIM. The SSIM parameter's values vary from 0 to 1, with 1 indicating identical frames and 0 indicating non-identical frames. After obtaining the frames, the SSIM is applied on the frame set to

remove the superfluous frames. SSIM is computed on different windows of a frame. Let, i and j indicates two images of common size $Q \times Q$ and is given as,

$$SSIM = \frac{(2\mu_i\mu_j + \alpha_1)(2\sigma_{i,j} + \alpha_2)}{(\mu_i^2 + \mu_j^2 + \alpha_1)(\sigma_i^2 + \sigma_j^2 + \alpha_2)} \quad (1)$$

where, μ_i represent mean value of i , μ_j represent mean value of j , σ_i^2 represent variance of i , σ_j^2 represent variance of j , $\sigma_{i,j}$ represent covariance of i and j , α_1 and α_2 denote constants.

Extraction of Neighborhood-based Features

Following the splitting of the image into frames, the features are taken from the frames. The characteristics of image such as neighborhood-based features are extracted effectively. The embedding can be done successfully by determining the best regions by extorting the features of key frame.

Neighborhood-based features: The purpose of neighborhood-based features is to search the pixel degree, based on several region-based characteristics, such as area, loop entropy, and edge information. This information is retrieved from frames. The area feature extracted from the frame is expressed as,

$$M_1 = \frac{1}{D} \sum_{c=0}^{D-1} P_{pq}^c \quad (2)$$

where, P_{pq}^c indicate neighbor pixel of P_{pq} , and D denote neighborhood. As a result, the edge information feature derived from frame is written as follows:

$$M_2 = \begin{cases} 1 & ; \text{if edgepixel} \\ 0 & ; \text{otherwise} \end{cases} \quad (3)$$

where, edge information is denoted by M_2 . The entropy of frame features is derived as follows:

$$M_3 = \frac{1}{E} \sum_{k=1}^E \varepsilon(I_k(p, q)) \quad (4)$$

where, E indicate number of regions, $\varepsilon(I_k(p, q))$ signifies energy of k^{th} location, and $I_k(p, q)$ denote loop of image.

Proposed WEWO Algorithm

The proposed WEWO-DeepRNN is employed to predict the pixels locations. Here, the DeepRNN is trained by proposed WEWO algorithm, which is amalgam of nature inspired optimization algorithms, WWO and EWO. Thus, the proposed WEWO-DeepRNN able to select optimum weights for pixel location.

Here, to obtain the optimal pixel location, the weights of DeepRNN classifier are trained by proposed WEWO. The weights are optimally selected to update the process. The EWA is motivated from the earthworm's reproduction process. The two kinds of reproductions are performed wherein reproduction 1 one offspring is produced by itself, and the reproduction-2, more than one progenies are produced at once and it is done by improving the reproduction operators, which is utilized for solving the optimization issues. The WWO is inspired from the shallow water wave theory and is effectively used for solving global optimization issues. The WWO portrays the phenomenon of water waves that includes refraction, propagation, and breaking which are utilized for deriving the effective method for searching huge dimensional solution space. The incorporation of EWA in WWO able to solve the optima issue and boost performance of proposed WEWO algorithm to obtain global optimum solution. The algorithmic methodology of proposed WEWO algorithm is given bellow:

Step 1) Initialization: In the initialization step, pixels of key frame are considered as possible solutions, which is given as,

$$Z = \{Z_1, Z_2, \dots, Z_\lambda, \dots, Z_\kappa\}; 1 \leq \lambda \leq \kappa \quad (5)$$

where, Z denotes key frame, Z_1 is first pixel, κ denotes total number of pixels or solutions.

Step2) Evaluation of the Error: The fitness value is computed using Mean Square Error (MSE) error criteria. When the difference between key frame image pixel and secrete image pixel is minimum, it is a potential optimal solution.

The MSE is formulated as follows,

$$MSE = \frac{1}{m \cdot n} \sum_{c=1}^{m \cdot n} [r_{(c,n)} - S_{(c,n)}]^2 \quad (6)$$

where, r is the key frame and S is the secrete image, c specifies number of video frames, where $1 < c \leq m, n$.

Step 3) Determination of weights: The EWO algorithm is utilized for solving the local optima issues. According to the EWO algorithm, the earthworms contained in the population poses the potential to reproduce offspring's and each earthworm poses two kinds of reproduction. The reproduction-1 phase is given as,

$$Z_{u,v}^{w+1} = Z_{\max,v} + Z_{\min,v} - \rho Z_{u,v}^w \quad (7)$$

where, ρ represent similarity factor which is a random number between 0 and 1, $Z_{\max,v}$ and $Z_{\min,v}$ represent upper and lower bound of position of earthworm u in v^{th} dimension, and $Z_{u,v}^w$ indicate current position of earthworm u in v^{th} dimension at time w .

In reproduction-2, some earthworms are capable to produce more than one individual at one time and are given as,

$$Z_{u,v}^{w+1} = \sum_{v=1}^Q \omega_v Z_{Ov} \quad (8)$$

where, ω_v represent weighting factor.

To solve local optima issues and enhancing the searching ability of earthworms, the addition of cauchy operator is done to the EWA algorithm. According to cauchy's mutation, the operation of Cauchy distributed function is given as,

$$Z_{u,v}^{w+1} = Z_{u,v}^w + W_j * M \quad (9)$$

where, $Z_{u,v}$ is the position of v^{th} position vector of u^{th} earthworm, M indicate cauchy operator which is a random number, W_j indicate the weighting factor.

In WWO, the refraction is carried out using waves whose heights reduce to zero and the update position after refraction is given as,

$$Z_{u,v}^{w+1} = Gaussian \left(\frac{Z_{best} + Z_{u,v}^w}{2}, \frac{Z_{best} - Z_{u,v}^w}{2} \right) \quad (10)$$

where, Z_{best} indicate best solution determined whose MSE is minimum. Gaussian is a random value with mean μ and standard deviation σ as 0, 1 and $Z_{u,v}^w$ is the current position of water wave at time w .

From EWO, as $\rho = [0,1]$. Thus, the expression of EWO and WWO is equated and given as,

$$\rho = Gaussian \left(\frac{Z_{best} + Z_{u,v}^w}{2}, \frac{Z_{best} - Z_{u,v}^w}{2} \right) \quad (11)$$

From equation (8), the value of similarity factor is expressed as,

$$\rho = Z_{u,v}^{w+1} \quad (12)$$

The proposed WEWO equation is obtained by substituting equation (12) in equation (7) which is given as,

$$Z_{u,v}^{w+1} = Z_{\max,v} + Z_{\min,v} - Z_{u,v}^{w+1} Z_{u,v}^w \quad (13)$$

$$Z_{u,v}^{w+1} + Z_{u,v}^{w+1} Z_{u,v}^w = Z_{\max,v} + Z_{\min,v} \quad (14)$$

$$Z_{u,v}^{w+1} (1 + Z_{u,v}^w) = Z_{\max,v} + Z_{\min,v} \quad (15)$$

The complete equation representing the proposed WEWO algorithm can be written as,

$$Z_{u,v}^{w+1} = \frac{Z_{\max,v} + Z_{\min,v}}{(1 + Z_{u,v}^w)} \quad (16)$$

It is observed from the equation that optimum weight is chosen using best solutions generated from the proposed WEWO to improve the performance. Thus, the output from the proposed WEWO algorithm is optimal weight, which can be used to discover pixel location to which the image is embedded.

Step 4) Error evaluation for update solutions: The obtained error values of generated offspring sare evaluated, where optimum weights are related to the minimum error.

Step 5) Terminate: The optimum weights are obtained till maximum iteration criteria are satisfied.

The performance of discovering optimum region is attained by combining the characteristics of both optimization algorithms.

Insertion of Secret Message with Wavelet Transform

After determining optimal pixel locations, the video steganography is preceded by implanting a undisclosed image within the chosen pixellocations. Embedding procedure is implemented to hide the secret image into the key frame. The wavelet transform technique is employed to hidding and abstraction of secret message. WT provides faster calculations than conventional transform methods. The key frame is divided into sixteen sub bands with two level decompositions. At first level of transform, the image is partitioned into four sub bands,LL, LH, HH, and HH. Then, the LL sub band is utilized for obtaining another level of decomposition. The secret information is entrenched within the low, middle, or high frequencies of the transformed coefficients. After embedding image, the IWT is adapted to embedded image for extracting the hidden data.

Results and Discussion

The effectiveness of proposed WEWO-DeepRNN using correlation coefficient, and Peak Signal to noise ratio (PSNR) is discribed. The analysis is performed by varying the number of frames. Moreover, the pepper noise and salt-pepper noise is added for computing the performance of method. (The implementation of proposed methodology is carried out in PYTHON using PC with Windows 10 OS, 2GB RAM, and Intel i3 core processor). The CAVIAR (2018) database is used for this work. The video clips were filmed for the CAVIAR database with a wide angle camera lens in the entrance lobby of the INRIA Labs at Grenoble, France. The resolution is half-resolution PAL standard (384 x 288 pixels, 25 frames per second) and compressed using MPEG2. The file sizes are mostly between 6 and 12 MB, a few up to 21 MB. CAVIAR video database is a set of small video clips recorded under various acts. In this work two video clips from the CAVIAR database are used for the comparative analysis.

Evaluation Metrics

The evaluation of the proposed WEWO-Deep RNN and other methods is performed with evaluation matrix namely Correlation coefficient and PSNR as defined below:

Correlation coefficient

The statistical relation between two variables is given as correlation coefficient and it ranges between -1 to +1 where in +1 represents strongest possible agreement and 0 indicates disagreement.

$$\gamma = \left(\frac{\sum (xi - \hat{x})(yi - \hat{y})}{\sqrt{\sum (xi - \hat{x})^2 \sum (yi - \hat{y})^2}} \right) \quad (17)$$

PSNR

Peak signal to noise ratio PSNR is a quality measure of images. It compares difference between original image and embedded image. PSNR is formulated as,

$$PSNR = 10 \cdot \log_{10} \left[\frac{Max(r_{(m,n)})^2}{\frac{1}{m \cdot n} \sum_{m,n} [s_{(m,n)} - r_{(m,n)}]^2} \right] \quad (18)$$

where, $r(m, n)$ indicates key images and $s(m, n)$ represent the embedded image.

Comparative Analysis

The analysis of methods is done using Correlation coefficient and PSNR parameters. Robustness is checked by adding pepper noise and salt-pepper noise and by altering key frames of a video.

Analysis of Video Case -1 and Video Case -2

The analysis of proposed method is performed using two random videos of CAVIAR dataset. Videos are mentioned as, video case -1 and video case -2, named view of the mall shop areas and walk by shop 1 corridor respectively. The video is in mp4 format.

The analysis based on Correlation coefficient and PSNR parameters is demonstrated with graphs.

Figure 1 is showing the comparison of methods considering pepper noise using CC and PSNR parameter with video case-1. When pepper noise is 0.05, the corresponding CC values evaluated by existing DWT+DCT, DCNN+DWT, DCNN+LSB and proposed WEWO-DeepRNN are 0.6240, 0.7832, 0.5924, and 0.7942. When pepper noise is 0.25, the CC values evaluated by existing DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 0.5852, 0.7588, and 0.7590.

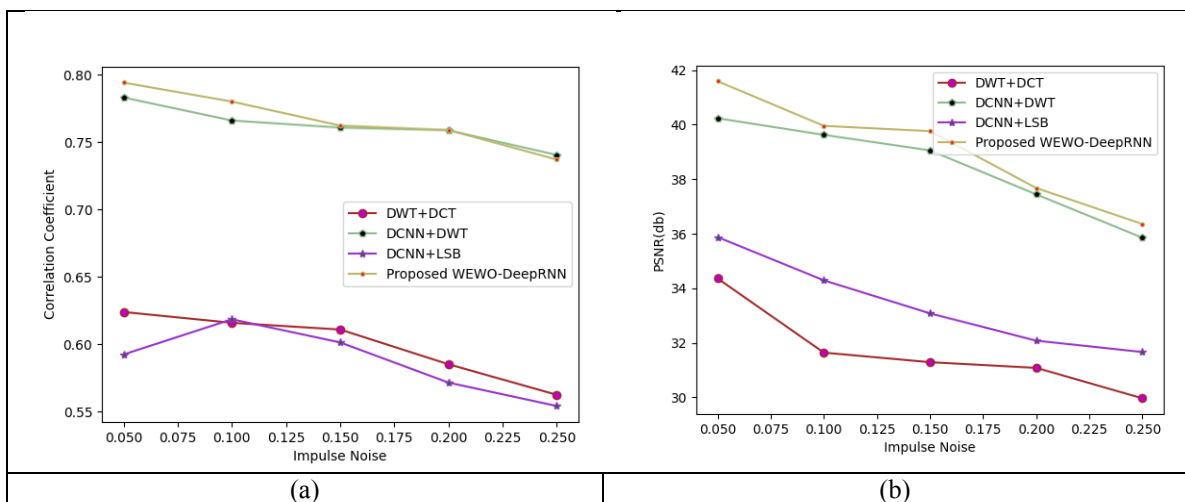


Figure 1. Analysis of Methods by Adding Pepper Noise Using a) CC b) PSNR

The comparison of methods using PSNR parameter is shown in figure 1b). When pepper noise is 0.05, the corresponding PSNR values evaluated by existing DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 34.36dB , 40.23 dB, 35.87dB, and 41.49 dB. When pepper noise is 0.25, the PSNR values evaluated by existing DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 29.97dB, 35.85dB, 31.66dB, and 36.35dB.

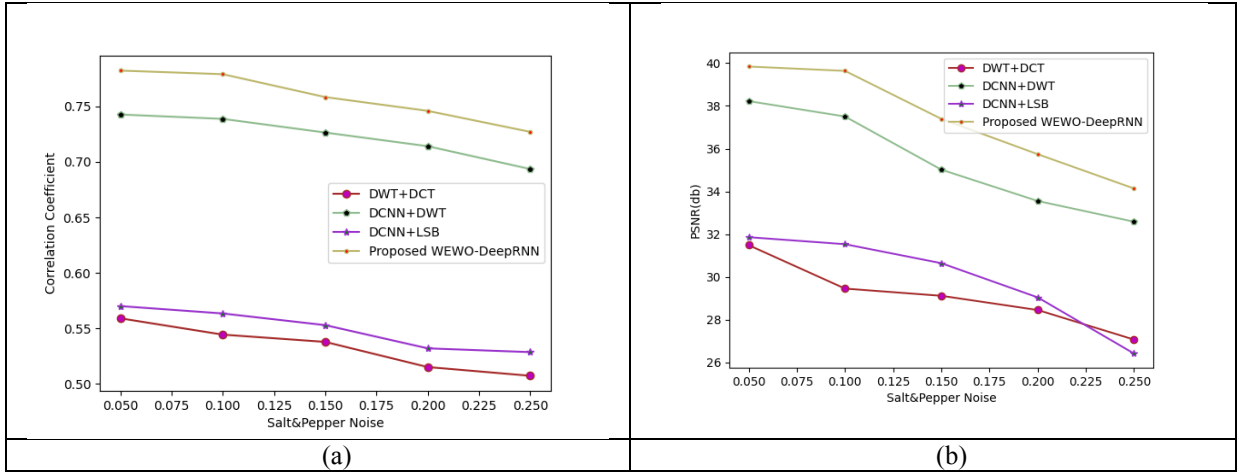


Figure 2. Analysis of Methods by Adding Salt-pepper Noise Using a) CC b) PSNR

Figure 2, showing the comparison of methods considering salt-pepper noise using CC and PSNR parameter with video case-1. When salt-pepper noise is 0.05, the corresponding CC values evaluated by DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 0.5591, 0.7427, 0.5701, and 0.7823. When amount of salt-pepper noise is 0.25, the CC values obtained are DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 0.5073, 0.6936, 0.5287, and 0.7270. When salt-pepper noise is 0.05, the PSNR values evaluated by existing DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 31.49dB, 38.22dB, 31.86dB, and 39.83dB. Likewise, when salt-pepper noise is 0.25, the PSNR values are DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 27.07dB, 32.58dB, 26.42dB, and 34.13dB.

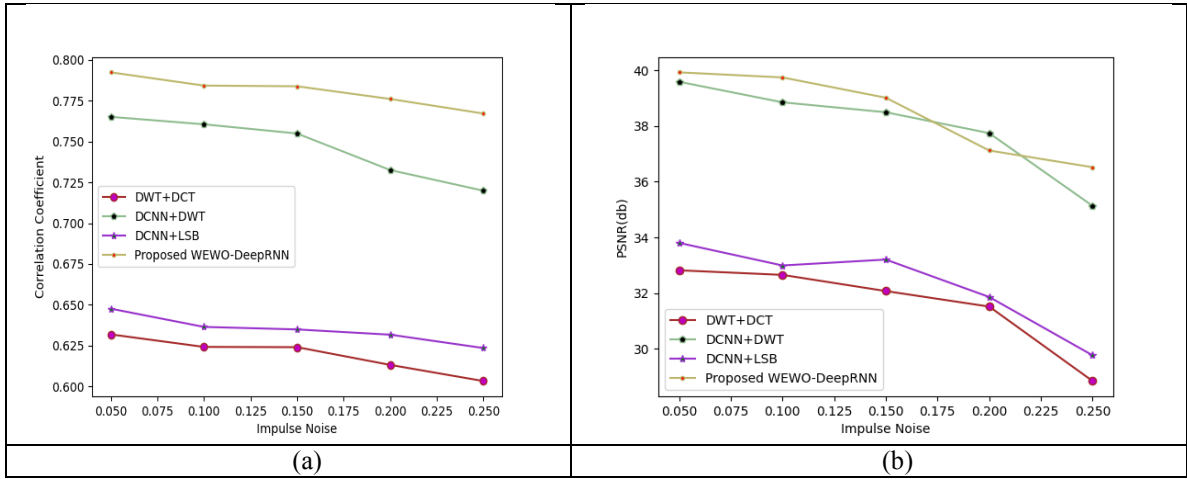


Figure 3. Analysis of Methods by Adding Pepper Noise Using a) CC b) PSNR

Figure 3 is showing the comparison of methods considering pepper noise using CC and PSNR parameter using video case-2. The comparison of methods using CC parameter is depicted in figure 3 a). When amount of pepper noise is 0.05, the corresponding CC values evaluated by existing DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 0.632, 0.765, 0.647, and 0.792. Likewise, when amount of pepper noise is 0.25, the CC values evaluated by existing DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 0.611, 0.720, 0.623, and 0.767. The comparison of methods using PSNR parameter is depicted in figure 3 b). When amount of pepper noise is 0.05, the corresponding PSNR values evaluated by existing DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 32.817dB, 39.59dB, 33.80 dB, and 39.93 dB. Likewise, when amount of pepper noise is 0.25, the corresponding PSNR values evaluated by existing DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 28.84dB, 35.13 dB, 29.76 dB, and 36.52 dB.

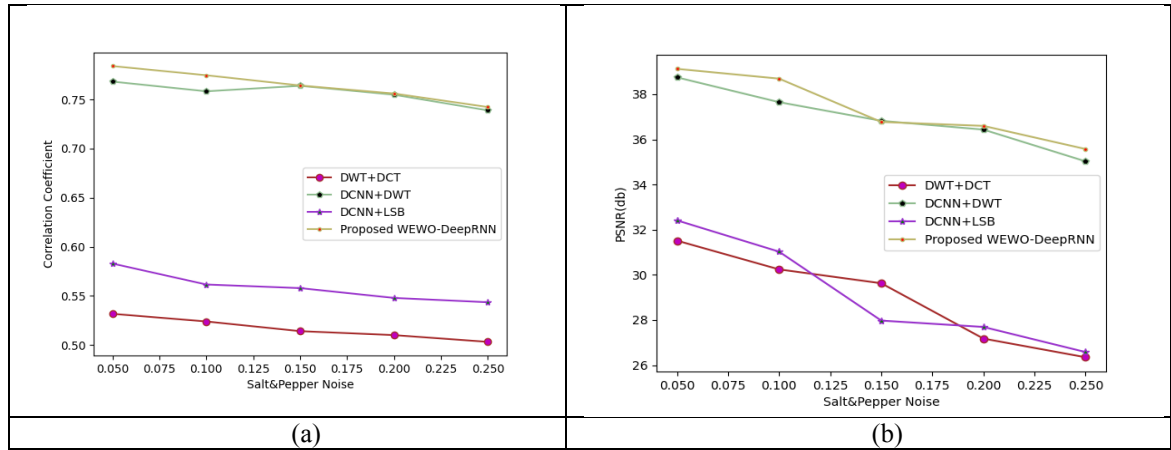


Figure 4. Analysis of Methods by Adding Salt-pepper Noise Using a) CC b) PSNR

Figure 4 showing the comparison of methods considering salt-pepper noise using CC and PSNR parameter with video case-2. When noise is 0.05, the corresponding CC values evaluated by existing DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 0.531, 0.768, 0.583, and 0.783. When noise is 0.25, the corresponding CC values are DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 0.506, 0.735, 0.544, and 0.742. Noise is 0.05, the PSNR values evaluated by existing DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 31.51dB, 38.74dB, 32.41dB, and 39.12dB. When noise is 0.25, the PSNR values evaluated by existing DWT+DCT, DCNN + DWT, DCNN+LSB and proposed WEWO-DeepRNN are 26.347dB, 35.03dB, 27.577dB, and 35.57dB.

Table 1 and 2, showing the comparison of DWT+DCT, DWT+DCNN, LSB+CNN methods with proposed WEWO- DeepRNN using CC and PSNR indexes. The analysis is carried out by varying the number of key frames. In addition, the pepper noise and salt-pepper noise is added for the robustness check of each method.

Table 1. Comparative Analysis for Video Case-1

Videos	Metrics	Variation	DWT-DCT	DWT+DCNN	LSB+CNN	Proposed WEWO-Deep RNN
Video case-1	Correlation Coefficient	Number of frames	0.7096	0.9584	0.9264	0.9660
		Pepper noise	0.5625	0.7403	0.5542	0.7765
		Salt-pepper noise	0.5327	0.7231	0.5494	0.7585
	PSNR (dB)	Number of frames	37.4399	41.3470	39.0976	41.8492
		Pepper noise	31.9468	38.4421	33.3987	39.0684
		Salt-pepper noise	29.2785	35.3763	29.9028	37.3491

Table 2. Comparative Analysis for Video Case-2

Videos	Metrics	Variation	DWT-DCT	DWT+DCNN	LSB+CNN	Proposed WEWO-Deep RNN
Video case-2	Correlation Coefficient	Number of frames	0.7073	0.9581	0.9301	0.9656
		Pepper noise	0.6210	0.7465	0.6339	0.7806
		Salt-pepper noise	0.5172	0.7571	0.5588	0.7642
	PSNR (dB)	Number of frames	35.7943	38.3608	35.6876	40.7439
		Pepper noise	31.5677	37.9642	32.3217	38.4681
		Salt-pepper noise	28.9465	36.9339	29.1143	37.3395

Conclusion

The proposed WEWO algorithm is used for tuning the optimal weights for predicting the pixels to which the secrete image is embedded. It provides optimum performance with maximal correlation coefficient of 0.973 and maximal PSNR is 43.87dB. This method can be extended by providing a steganographic method which is able to incorporate other privacy mechanisms like error correcting codes or cryptography.

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