Uncompressed Video Watermarking Using Motion Vectors and Back Propagation Network

Dr. Anurag Mishra
Department of Electronics
Deendayal Upadhaya College
University of Delhi, India

Monika Srivastava
M. Tech
Electronics & Communication
GGSIP University, Delhi, India

***Abstract*- We propose a new digital video watermarking scheme based on motion vector analysis in this paper. For this purpose, an uncompressed AVI video is taken as input and logo watermark is embedded into the frequency domain of the blue channel of the selected video frames using Back-Propagation neural network (BPN). The BPN will learn the characteristic of the frame and then the watermark is embedded and extracted by using the trained BPN. Block matching algorithm is used for selection of frames having maximum motion in X and Y directions from the video. This process prevents possible pirates from removing the watermark easily. Robustness studies are carried out by executing three video processing attacks. The results indicate that the proposed watermarking scheme successfully carries out both embedding and extraction of watermarks. The proposed scheme is also found to be robust against the selected attacks. Moreover, time complexity analysis shows that the scheme is suitable for real time watermarking applications**

Keywords—Motion Vectors Analysis, Block Matching Algorithm, DWT, Back Propagation Neural Network, Video Watermarking

I. INTRODUCTION

As we see in past several years, the communication and circulation of digital multimedia content like images, audio and video have become very easy using powerful internet technologies. But, at the same time, the threats of copyright violation and destruction of digital content has become the order of the day. Therefore, it has become necessary to legally protect digital content by applying robust copyright protection and authentication schemes. Digital watermarking of multimedia content is one such solution. The basic procedure of digital watermarking is to embed some kind of encrypted digital information into host multimedia data, while the quality of the watermarked data is retained, and the watermark can still be detected under different kinds of intentional and unintentional attacks. The watermarking techniques must fulfill the twin criteria- visual quality of watermarked frame and the robustness of the embedding algorithm. These two criteria are mutually exclusive. If we intend to increase robustness, it can be done at cost of decreased visual quality of the signed content. Moreover, real time constraints are required to process a given compressed / uncompressed video at run time. In view of this, fast executing watermark embedding and extraction schemes are much in demand. A variety of watermarking algorithms have been proposed in the literature. These algorithms can be classified in two categories according to the embedding domain: spatial and frequency domain. While frequency domain approaches usually result in robust watermark embedding as the watermark is inserted in low or mid frequency band coefficients which contribute the most to the signal. Especially, DWT based watermarking techniques are gaining more popularity due to their excellent spatial localization, frequency spread, and multi-resolution characteristics. The DWT is more computationally efficient and faster than other transform methods [1- 3].

Akhil et al. [1] propose a robust image watermarking technique based on 1-level DWT (Discrete Wavelet Transform). This method embeds invisible watermark into salient features of the original image using alpha blending technique. Experiment result shows that the embedding and extraction of watermark depend only on the value of alpha. All the results obtained for the recovered images and watermark is identical to the original images.

G. Bhatnagar et al [2] presented a semi-blind reference watermarking scheme based on discrete wavelet transform (DWT) and singular value decomposition (SVD) for copyright protection and authenticity. Their watermark was a gray scale logo image. For watermark embedding, their algorithm transformed the original image into wavelet domain and reference sub-image is formed using directive contrast and wavelet coefficients. Then, their algorithm embeds the watermark into the reference image by modifying the singular values of reference image using the singular values of the watermark

Faragallah [3] presents an efficient, robust and imperceptible video watermarking technique based on SVD decomposition performed in DWT domain. In this paper, two levels of high frequency band HH and mid-frequency band LH are SVD transformed and the watermark are hidden into them. Their proposed algorithm is tested in the presence of image and video processing attacks and their experimental results prove that this method survives these attacks. They attribute these positive results to the amalgamation of DWT and SVD transforms they use in their work.

At present the focus of research on video watermarking is limited to three main issues. These are visual quality of signed video, robustness and watermark embedding capacity The former two are optimized to obtain robust embedding and extraction schemes. To this end, several researchers

IJERT

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

ISSN: 2278-0181
Vol. 3 Issue 8, August - 2014

worldwide have extensively relied upon the use of artificial neural network (ANNs) to implement image and video watermarking [4-6].

Huang et al. [4] have proposed a novel blind watermarking technique based on back-propagation neural network. In this paper, a scrambled watermark is hidden into an image. HVS characteristics are taken into consideration during the watermark embedding process, The algorithm then uses the back-propagation neural network to learn the characteristics of the embedded watermark and the watermarked image. The authors argue that with the aid of learning and adaptive capabilities of neural network, the trained neural network can exactly recover the watermark from the watermarked image.

Xuefang Li et al. [5] propose a novel digital video watermarking scheme based on 3D DWT and artificial neural network. They embed the watermark in LL sub band of DWT coefficient after applying 3D DWT on each selected video shots. The authors claim that the proposed scheme is robust to selected video processing attacks. In this case, a neural network is used to memorize the relationship among the coefficients in 3x3 block of frame.

Maher EL'ARBI et al. [6] have developed a novel video watermarking algorithm based on Multi resolution motion estimation and artificial neural network. In this paper motion estimation algorithm is adopted to preferentially allocate watermark to coefficient containing motion .A BPNN is used to memorize the relationship between coefficients in 3x3 block of image.

Hartung et al. [7] published one of the pioneering works for watermarking of compressed and uncompressed video. They embed an encrypted pseudo-noise signal as watermark within the MPEG-2 encoded video to obtain an invisible, statistically unobtrusive and robust scheme. Their scheme is also found to work for other hybrid transform coding schemes like MPEG-1, MPEG-4, H.261 and H.263. For processing of their frames, they have used DCT method within their algorithm. They have also delved upon the issue of time complexity of their embedding algorithm vis-à-vis other methods.

Biswas et al. [8] have presented a new compressed video watermarking procedure which embeds several binary images as watermarks decomposed and obtained from a single watermark image into various scenes of the subject MPEG-2 encoded video sequence. Their scheme is found to be substantially more effective and robust against spatial attacks such as scaling, rotation, frame averaging and filtering besides temporal attacks like frame dropping and temporal shifting.

In this paper we propose a BPN based approach to implement watermarking of frames of three given standard uncompressed video using there motion vector computation. The selected video are all comprised of 100 frames. A frame selection criterion is applied to select 10 frames for watermark embedding. A data set is developed by using the LL3 sub band coefficients obtained after applying 3 level DWT on the blue channel of the selected video frame. The BPN neural network is trained using this data set which produces a row vector of normalized coefficients. A binary watermark is embedded with in these coefficients of the row vector so as to obtain signed video frames .The frames are reorganized with in the video so that the resultant video becomes watermarked video. Extraction of the watermark is also carried out by using reverse process and yields high NC and low BER. The signed video sequence is found to be of good visual quality after watermark embedding as indicated by high PSNR.

The watermarked video is examined for robustness by applying selected video processing attacks. The attacks used in present work are (a) Scaling (b) Gaussian Noise and (c) JPEG Compression. The watermarks are successfully extracted from attacked frames. It is concluded that the proposed motion vector and BPN training based watermarking scheme is found to be suitable for developing real time watermarking applications. The rest of paper is organized as follows: The Block matching algorithm is explained in section 2. Section 3 illustrates the architecture and training of BPN network. It also describes the embedding and extraction processes in detail. The experimental results are presented in section 4. Finally, the conclusions are given in section 5.

II. ARCHITECTURE OF BPN

The advantage of neural network is that, they are best suited to solve the problem that is most difficult to solve by traditional methods. The BPN is a kind of supervised learning neural network. Its learning process work in small steps: Input is applied to the network; the network produces some output based on current state of weights. This output is compared with known output and mean square error signal is calculated. This error value is then back propagated through the network and small changes in weights are made in each layer. The cycle is repeated until error signal drops below threshold. It is one of the most frequently used learning techniques in neural networks. A general model of the BPN is represented in Fig. 1.

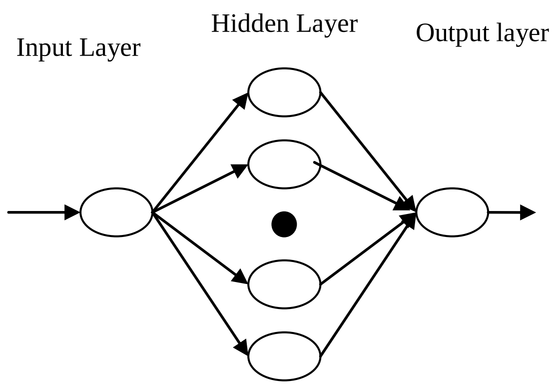


Fig.1: BPN Architecture

There are three layers including input layer, hidden layer, and output layer. Two nodes of each adjacent layer are directly connected to one another, which is called a link. Each link has a weighted value, which represents the relational degree between two nodes. A training process described by the (1) updates these weighted values.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

$$net_j(t)=\sum_i \alpha_{i,j} o_i(t)-\theta_j$$
$$o_j(t+1)=f_{act}(net_j(t)) \quad (1)$$

where $net_j(t)$ is the activation value of the node j in iteration t , $o_j(t+1)$ is output of the node j in iteration t +1, $f_{act}(x)$ is called the activation function of a node, which usually is a sigmoid function in hidden layers and a pure line function in output layer. Generally, all initial weight values $\alpha_{i,j}$ are assigned using random values. In each iteration process, all $\alpha_{i,j}$ are modified using the delta rule according to the learning data.

A. BPN Training Procedure

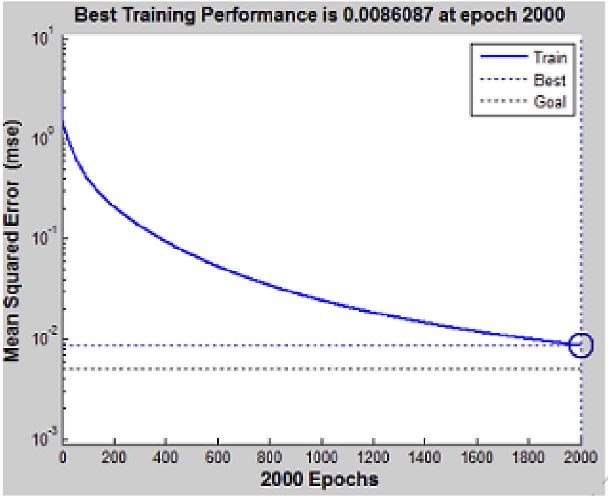


Fig.2: BPN Training Procedure

First, all frames are extracted from the given uncompressed video sequence. Then, 3-level DWT is applied on the blue channel of the selected frames one by one. The quantization with a pre-selected Q value is done after this step. The factor round (CA3 (i, j) / Q), where CA3(i, j) is the 3 level decomposed low frequency band coefficients, is represented as P and is used as an input for the BPN and T (Target) is used as a desired output value given by network. The 3 layer structure of the BPN network with 1 input, 1 output and 1 hidden layer having 65 neurons in the intermediate layer is used in this work. The hidden layer and output layer uses sigmoid and pure line activation functions respectively. The training method is based on Levenberg - Marquardt rule whose training error is set to be 0.005. The number of maximum learning iteration is set to be 5000. When either the training error becomes smaller than 0.005 or the iteration is reached to the maximum iteration number, the training is finished. Fig. 2 shows the training error in each step when the BPN is trained using all CA3 (i, j) coefficients of blue channel of the 256 x 256 size frame of the selected uncompressed video. The BPN trained by this method will be used to embed and extract the watermark.

III. EXPERIMENT DETAILS

Firstly, an uncompressed video of 100 frames is taken as input and divide it into non overlapping frames of size M x N. Secondly, the block matching algorithm is used for calculation of motion vectors of all frames. After this, a frame selection criterion is applied for selecting frames of maximum motion. A logo image of 32*32 is taken and embedded as a watermark in these selected frames using back propagation neural network. After embedding, the logo image becomes invisible and will not be distinguished by eyes. This technique belongs to the category of blind watermarking algorithms.

A. Frame Selection Criteria

While embedding the watermark into an uncompressed video, it is observed that to obtain the complete video signed by using this procedure is a bit costly in time. Therefore, we decide to apply a selection criterion on frames. Under this criterion, not more than 10% of the frames of the given video are actually watermarked. Listing 1 gives the algorithm for frame selection criterion based on block matching algorithm which computes the motion vector for the frames of the given video sequence

Listing 1: Algorithm for frame Selection

Step 1: An uncompressed video is taken as input and divide it into RGB frames of size M x N.

IJERT

Step 2: These frames are subject to Full search block matching algorithm for computation of its motion vectors.

Step 3: As a result of step 2, the magnitude of motion vector range is found in between 0 to 98. Then, the locations having motion vector magnitudes greater than 75 are selected by keeping a threshold of 75.

Step 4: Finally, select a 10% combination of total frames having maximum motion amongst the entire set of frames for watermark embedding. This step may yield a variable number of frames to be watermarked depending upon the type and nature of video.

B. Watermarking Embedding

The watermark embedding algorithm is given in Listing 2.

Listing 2: Algorithm for Watermark Embedding

Step 1: Apply the 3-level DWT transform using Haar filter on the Blue channel of each selected RGB frames of video. CA3 (i, j) is the LL3 sub band coefficients when DWT transform is performed on Blue channel of a selected frame.

Step 2: Quantize the DWT coefficient CA3 (i, j) by Q and reshape it into row vector of size 1x1024.

Step 3: Train the BPN neural network using the data set generated in step 1, 2 and obtain an output row vector T1′ of size 1x 1024

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

Step 4: Embed the watermark according to the (2) which uses the output value T1′ and the Q

If W=1
C2′ = T1′ + alpha*(Q/4)
Else
C2′= T1′ - alpha*(Q/4) (2)

Step 5: To get watermarked blue channel, apply inverse DWT or IDWT on C2' where watermark is embedded. The concatenation of Red, Green and Blue channels finally gives (R G B) frames which results in the watermarked video sequence.

Step 6: All the frames are reorganized with in their respective position in original video. So the resultant video becomes watermarked video.

Fig. 3 depicts the block diagram of watermark embedding procedure

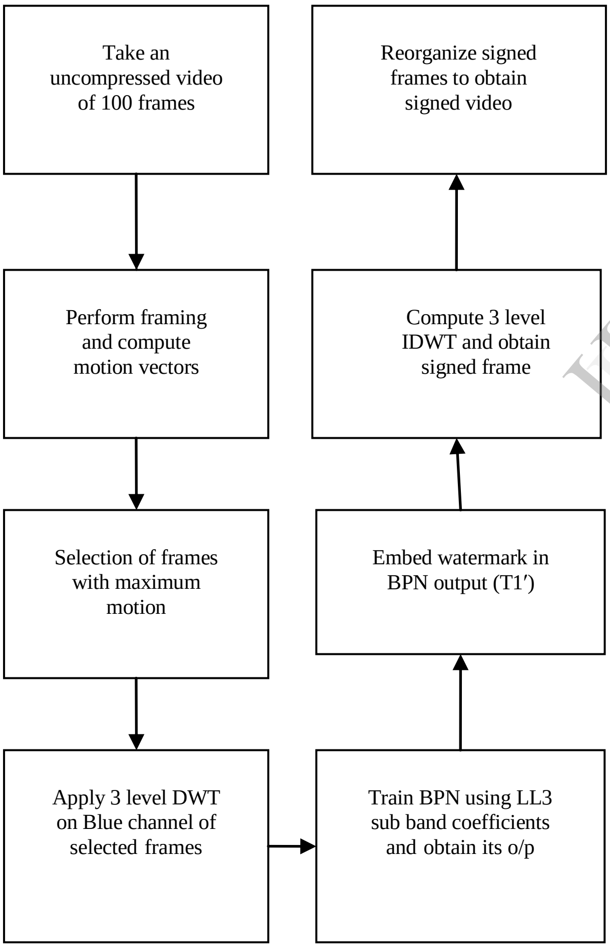


Fig.3: Block Diagram of watermark embedding scheme

The visual quality of watermarked frames of the video is quantified by computing average PSNR and is calculated using formulation given in (3).

$$AVG\_PSNR = \frac{\sum_{i=1}^{T} PSNR}{T} \quad (3)$$

Where T = Total number of frames in video. This equation uses Peak Signal to Noise Ratio (PSNR) which measures the imperceptibility of the watermarked frame. The PSNR of the watermarked frame is calculated using the (4).

$$PSNR = 10\log_{10}\frac{255^2}{MSE} \quad (4)$$

where Mean square error (MSE) is given by (5).

$$MSE = \sum_{j=1}^{r}\sum_{k=1}^{c}\frac{I(j,k)-I'(j,k)}{rc} \quad (5)$$

where r = number of rows in the frame
c = number of columns in frame
I (j, k) = original frame
I′ (j, k) = watermarked frame

C. Watermark Extraction

The watermark extracting procedure is exactly opposite to one used in embedding. The BPN in this case is a trained neural network, which is discussed in section 3. Q is the quantization value.

Fig. 4 depicts the block diagram of the proposed video watermark extraction algorithm.

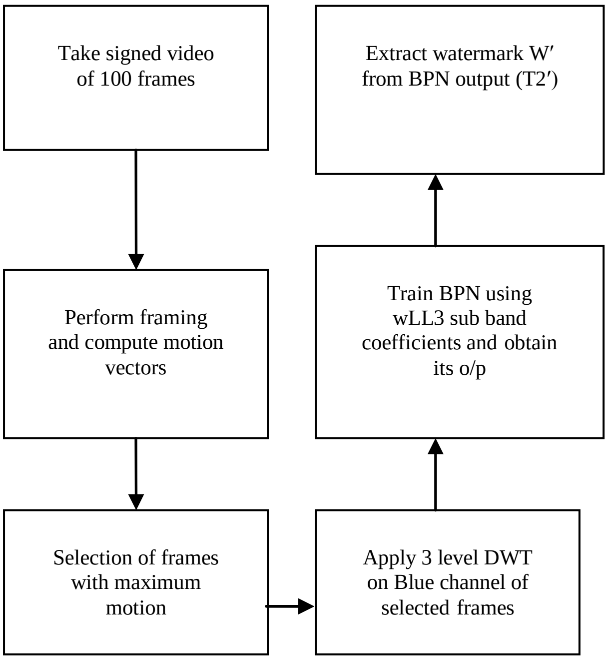


Fig.4: Block Diagram of watermark extraction scheme

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

The normalized correlation coefficient (NC) and Bit Error Rate (BER) is used to measure the similarity between the embedded watermark and the recovered one. For this purpose NC and BER are computed using Eqns. 6 and 7 respectively.

$$NC = \frac{\sum_{i=1}^{x}\sum_{j=1}^{y}[W(i,j).W'(i,j)]}{\sum_{i=1}^{x}\sum_{j=1}^{y}[W(i,j)^{2}]} \qquad (6)$$

$$BER = \frac{1}{xy}\sum_{j=1}^{xy}\left|W'(j)\text{-}W'(j)\right| \qquad (7)$$

Where
W (i, j) = original watermark
W′ (i, j = Extracted watermark

The extraction algorithm is given in Listing 3

Listing 3: Algorithm for Watermark Extraction

Step 1: Firstly take signed uncompressed as input and divide it into frames of size M x N

Step 2: Apply frame selection criteria to select watermarked frames of maximum motion from all the frames

Step 3: Extract the Blue channel from the selected watermarked (R G B) frame then perform a 3-level DWT using Haar filter on the Blue channel. wCA3 (i, j) is the LL3 sub band when DWT is applied on the Blue channel

Step 4: Quantize the DWT coefficient wCA3 (i, j) by Q, and use it as input value of the trained BPN to get the output T2′

Step 5: Extract the watermark using the (8) below, using the output T2′ and coefficient wCA3 (i, j)

$$W = \begin{cases} 1 & wCA3\ (i, j) > T2' \\ 0 & \text{otherwise} \end{cases} \qquad (8)$$

IV. EXPERIMENTAL RESULTS

The performance of the proposed watermarking algorithm is evaluated on three standard uncompressed video sequences namely Car, Suzie and Foreman in AVI format having frame rate of 30fps and each consisting of 100 frames. A logo watermark is embedded in Blue channel of selected frames by using trained BPN network

Table 1: Frames selected in video using adopted frame selection criteria

Video	Selected Frames for Watermark Embedding								
Car	4	12	19	27	34	42	49	59	
Suzie	47	50	53	56	59	62	65	71	
Foreman	2	44	58	70	75	82	88	92	100

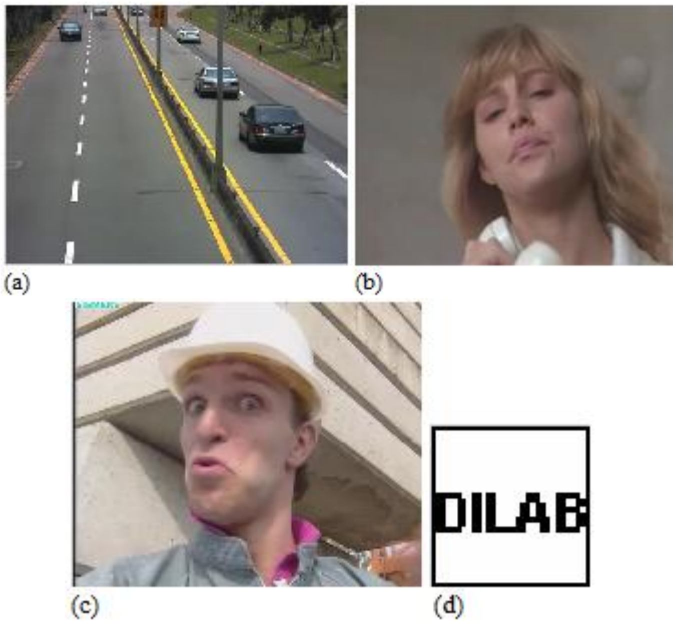


Fig. 5(a-d): Central frame of selected video frames of (a) Car, (b) Suzie and (c) Foreman respectively and (d) the Original binary watermark

IJERT

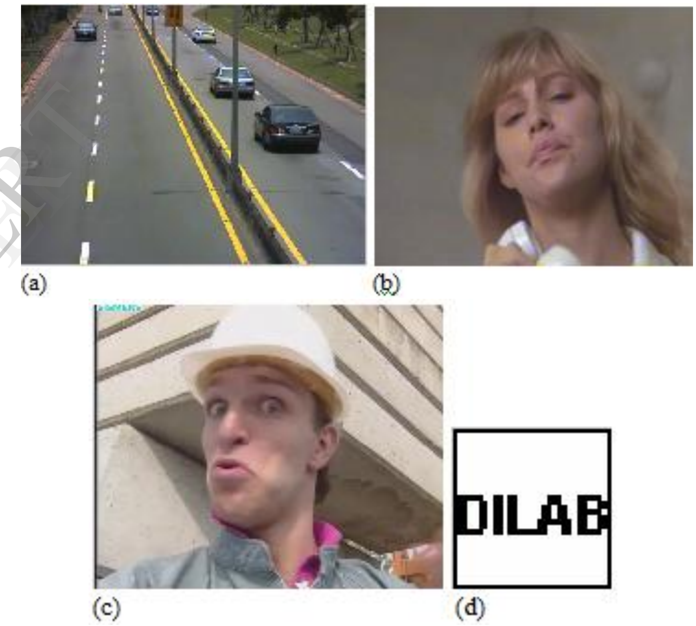


Fig. 6(a-c): Watermarked video frame of (a) Car, (b) Suzie and (c) Foreman respectively and (d) the extracted watermark

Table 2: Time (in seconds) consumed in embedding and extraction of watermark in one frame

For one frame	Car	Suzie	Foreman
Embedding time (secs)	12.26	7.06	6.56
Extraction time (secs)	0.203	0.218	0.203
Total time (secs)	12.463	7.278	6.76

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

Table 1 depicts the frames selected for watermark embedding using frame selection criteria in video sequences Car, Suzie and Foreman respectively. Fig. 5(a-c) depicts the central frame of selected frames of video sequence Car, Suzie and Foreman respectively. Fig. 5-d depicts original watermark. Fig. 6(a-c) depicts signed frames respectively and Fig. 6 (d) depicts the extracted watermark. The average PSNR in our simulation is 42.27dB 50.3dB and 46.23dB respectively for Car, Suzie and Foreman sequence. We further report high values of NC (Normalized cross correlation) for all three videos. The computed value of NC value in our work is 0.998, 0.997 and 1 for these three video respectively. After that we obtain BER values as 0.002, 0.04 and 0 respectively. These results show that the proposed watermarking scheme successfully carries out embedding and extraction processes. To analyze the issue of time complexity we take into account total time for embedding and extraction of watermark in one frame of all three videos given by Table 2.

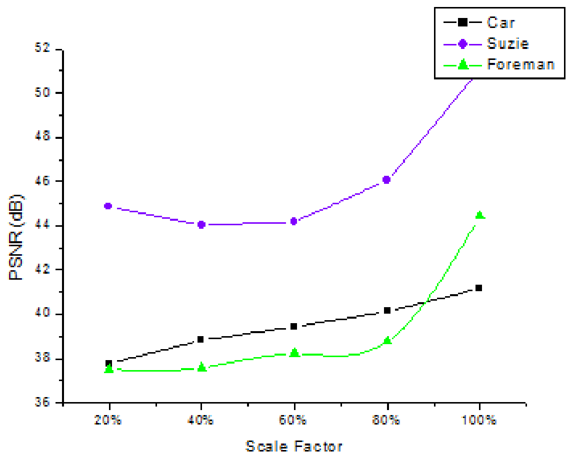
To examine the robustness of proposed watermarking scheme three video processing attacks are carried out on the watermarked video sequence. PSNR, NC and BER are calculated with respect to variation in respective attack parameter and plots are shown in Figs. 7, 8 and 9

(a) Scaling: In this case, the video frames are scaled up to different sizes of the signed frame and reverted back. These sizes are 20, 40, 60, 80, 100%. Fig. 7(a-c) respectively shows the plot of PSNR (dB), NC (W, W′) and BER (W, W′) w. r. t different scaling size. A large value of PSNR and NC clearly indicates that the proposed watermarking algorithm resists the scaling attacks.

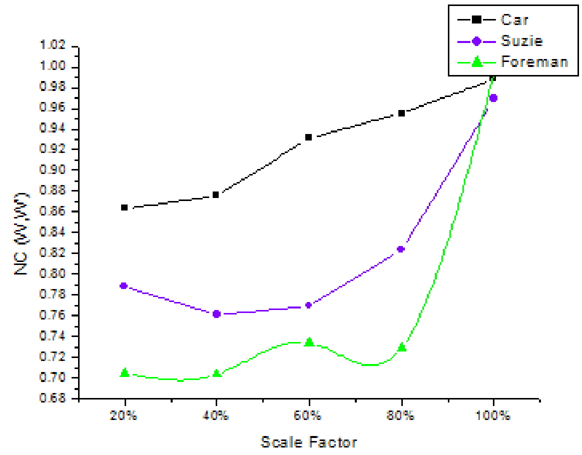
(b) Gaussian Noise: This noise is added to watermarked frame by taken mean 0 and variance as 0.0001, 0.0002, 0.0003, 0.0004, 0.0005, 0.0006 and 0.0007. Fig. 8 (a-c) shows the plot of PSNR (dB), NC (W, W′) and BER (W, W′) w. r. t noise variance.

(c) JPEG Compression: As the original video is available in RGB uncompressed AVI format, it is subjected to JPEG compression also. Fig. 9(a-c) shows the plot of PSNR(dB), NC (W,W′) and BER(W, W′) w. r. t quality factor = 70, 75, 80, 85, 90 and 95.

(a)



(b)



(c)

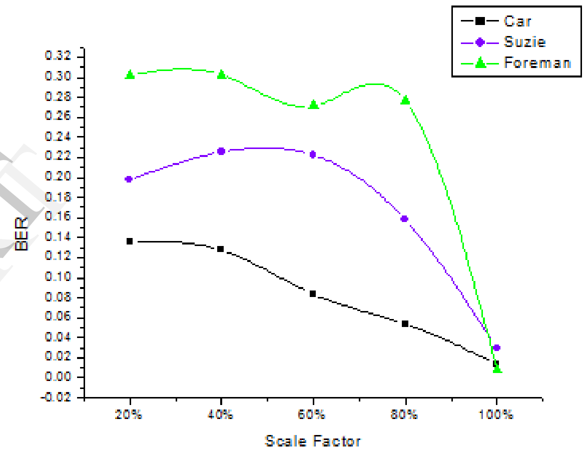
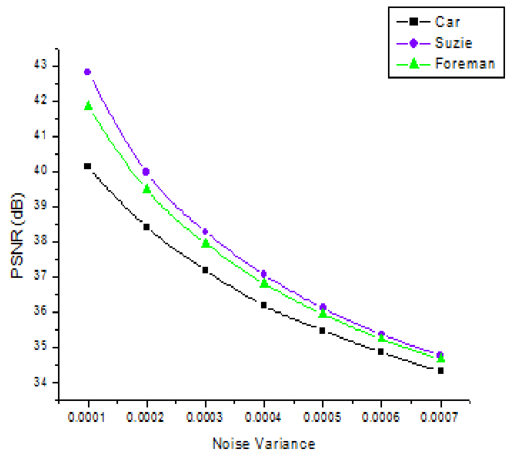


Fig.7 (a-c): Plot of PSNR (dB), NC and BER w .r .t scaling factor

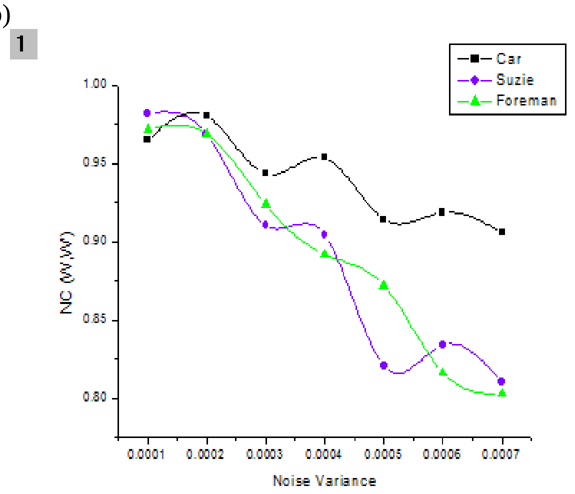
(a)



IJERT

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

(b)



(c)

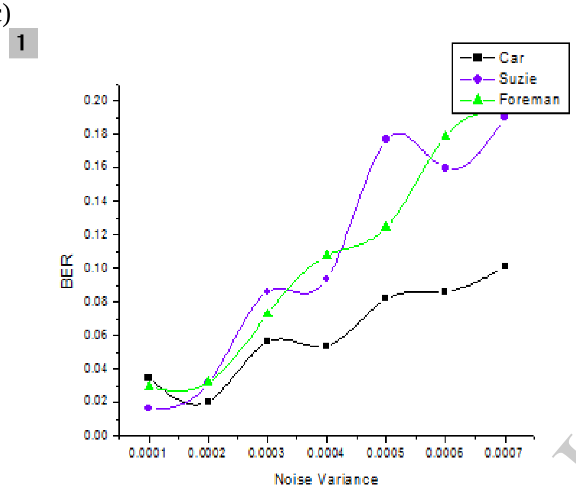
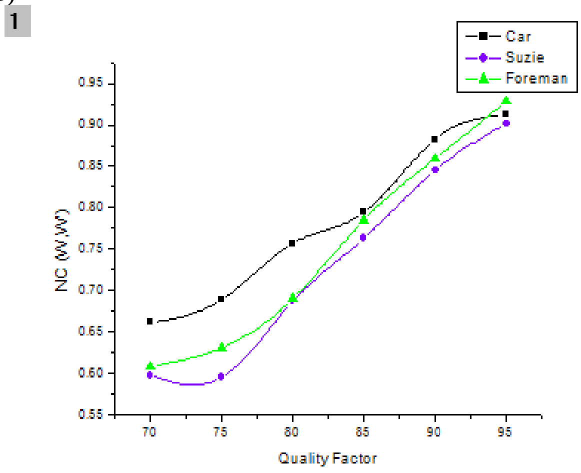


Fig. 8(a-c): Plot of PSNR (dB), NC and BER w. r. t Gaussian noise density

(b)



(c)

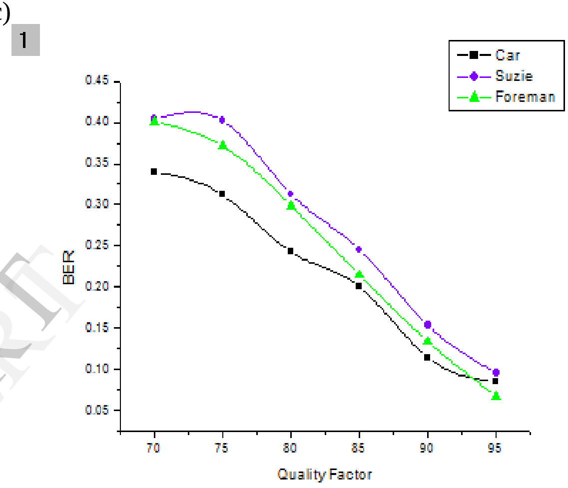
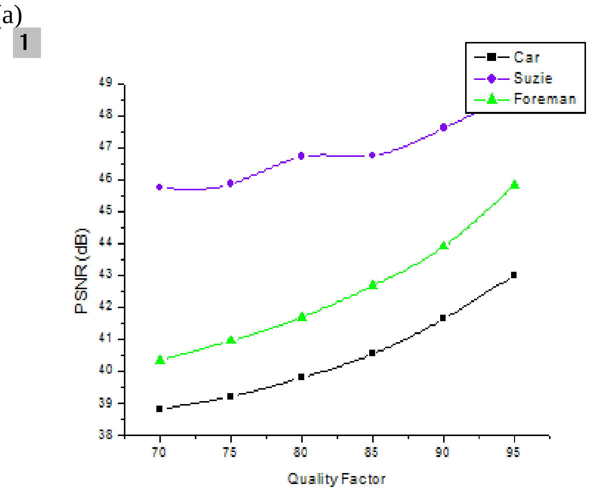


Fig. 9(a-c): Plot of PSNR (dB), NC and BER w. r. t Quality factor

IJERT

(a)



V.CONCLUSION

In this paper, a new video watermarking scheme that uses motion vector calculation for watermark embedding has been proposed. Appropriate frames are selected using Block Matching Algorithm having criteria of maximum motion. The proposed method embeds a logo watermark into the DWT coefficient of blue channel of the selected RGB frames. This process prevents possible pirates from easily removing the watermark. The embedding scheme has good quality of the watermarked image in terms of PSNR. We also use back-propagation neural networks (BPN) which is used to learn the characteristics of the original frame for watermark embedding. Due to the learning and adaptive capabilities of the BPN, the embedding / extracting strategy can greatly improve robustness to various attacks. Experimental results indicate that the performance of the proposed technique is superior to other methods in the literature and it is significantly robust against scaling, noise addition and video compression attacks.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

REFERENCES

[1] Akhil Pratap Singh and Agya Mishra, Wavelet Based Watermarking on Digital Image, Indian Journal of computer Science and Engineering,Vol.1 No 2, pp. 86-91, 2011.

[2] G. Bhatnagar and B. Raman, A new robust reference watermarking scheme based on DWT-SVD, Computer Standard and Interfaces 31(5), pp. 1002-1013, 2009.

[3] O.S. Fargallah, Efficient video watermarking based on singular value decomposition in the discrete wavelet transform domain. AEU Int. J. Electron. Commun. 67(3), 189–196 (2013)

[4] W. Hong and M. Hang, Robust Digital Watermarking Scheme for Copy Right Protection, IEEE Trans. Signal Process, vo.l2, pp. 1- 8, 2006.

[5] Xuefang Li, Rangding Wang, A Video Watermarking Scheme Based on 3D-DWT and Neural Network. ISMW Proceedings of the Ninth IEEE International Symposium on Multimedia Workshops, pp. 110-115, 2007.

[6] M. EL'Arbi, C. B. AMAR, and H. Nicolas, 'Video watermarking based on neural networks. ICME 1577-1580(2006)

[7] F. Hartung, B. Girod, Watermarking of uncompressed and compressed video. Sig. Process. 66(3), pp. 283–301, 1998

[8] S. Biswas, E.M. Petriu, An adaptive compressed MPEG-2 video watermarking scheme. IEEE Trans. Instrum. Measur. 54(5), 1853–1861 (2005)

[9] J Breezy and L Rowe, "Comparison of video shot boundary detection techniques", Proc. SPIE Conference on Storage & Retrieval for Still Image & Video Databases IV, Vol. 2670, 1996

[10] M. Ishtiaq, M. Jaffar , M. Khan, Z. Jan, and AM. Mirza ,Robust and Imperceptible Watermarking of Video Streams for Low Power Devices, Communication Computer Information Science, pp. 177-184, 2009.

IJERT

(This work is licensed under a Creative Commons Attribution 4.0 International License.)