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High Efficient Video Coding through improved Holo Entropy Encoding with Hybrid Grey wolf Optimization

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Abstract: Advanced video coding (AVC) is lion's share concept in present video compressing technology. In this regard, High Efficiency Video Coding (HEVC) delivers almost double of the data compression similar to the original video quality without variation in the bit rate.In this paper a novel enhanced holoentrophy is proposing for accomplishing encoding process in HEVC by linking with proposing tansig transfer function. Enhanced holoentrophy is the enhanced entropy standard where all the pixel deviations are grouped based on the interest and outliers will be eliminated. The weightage of tansig transfer function is optimally tuned through Hybrid Grey Wolf Optimization (HGWO) algorithm. To reduce the search space in GWO optimization GA optimization algorithm is used therefore this mechanism is named ad Hybrid Grey wolf Optimization. In the last, the proposed encoding technique is compared with conventional encoding techniques in terms of Root Mean Square Error (RMSE), Structural similarity index (SSIM) and Universal Quality Index (UQI) .

Keywords: AVC, HEVC, Holoentrophy, Tansig function, GWO, SSIM, RMSE and UQI

1. INTRODUCTION

Video compressing is most requisite application in modern technology especially for data propagation through the internet. In this regard, conversion of high bit rate data into low bit rate in transmission process without losing the original content. Meanwhile various types of compressing techniques have been using for compression of the video information.Generally, Motion Compensation (MC) and Discrete Cosine Transform (DCT) are the existing techniques for video coding and H.26,MPEG are the video coding standards. As it is known fact that AVC is also known as MPEG-4 part 10 or H.264 and it is based on the motion-compensated integer DCT coding and blockoriented. Whereas HEVC is based on the motion compensated integer DCT and DST from the block sizes (4×4, 8×8, 16×16, 32×32). In this paper a novel technique for HEVC encoding process is being proposed that is called as Holoentrophy. In this process the weight of the Tansig function is tuned through Grey Wolf Optimization (GWO) Algorithm [6-10]. The overall structure of this paper is categorised into V sections. Section II deals about Literature survey, section III deals with the architecture of HEVC, section IV deals with the proposed HEVC encoding process based on the novel technique Holoentrophy through the Grey Wolf Optimization Algorithm and Section V deals with the results and discussions.

2. HEVC model with Standard Architecture

The HEVC deploys the intra and inter image prediction model based on "video compression" principles. Spatial significance could be found out among the picture frame sections in intra prediction model [1-5]. Whereas reference frame relating the association of frames in inter type and it portrays motion vector. HEVC is a novel technique in video compressing application and it has standardised with ITU-T and ISO/IEO MEPG [1]. It is better than AVC/M.264 in terms

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of coding gain up to 50%. HEVC architecture is illustrated in fig. 1. As shown in fig.1Encoder is nothing but duplicate decoder which is used to reconstruct the

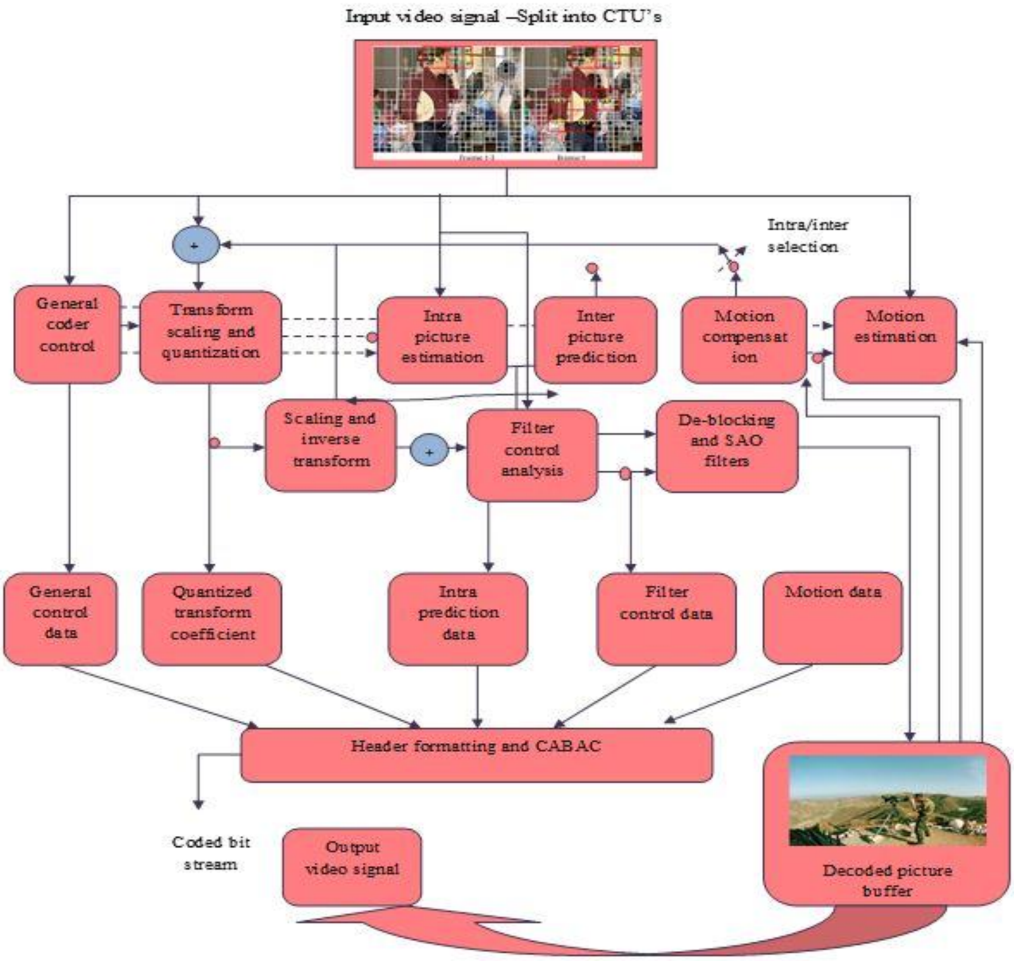

Fig 1 Standard architecture of HEVC model

approximated residual signal by performing both the transformation and scaling functions. The subsequent frames of the images could be predicted relating with the duplicate decoder output which is stored by decoded picture buffer. It includes very interesting features and essential components [13-15] like coded tree block (CTB), coded tree unit (CTU), coded block (CB) and coded unit (CU). And it also contains prediction blocks (PB), prediction units (PU), transmit blocks (TB), transmit units (TU), quantization, intra-picture prediction, entropy encoding, sample adaptive offset and in-loop de blocking filter. In HEVC architecture CTU function is same macroblock in existing coding standard and it is higher in size also. Syntax elements, associated chroma CTBs and luma are exist in the CTB unit [11-13].Generally, CTB are portioned into quadra tree signalling and tree structure based on minor blocks and it is also larger in size. The maximum size in both luma CB and CTB is same and one CU is formed by two chroma CBs and one luma CB. CTB may consists one CU or multi-CUs and each CU could be divided into TUs and PUs. Advanced multi vector processing is incorporated in multi vector (MV) signalling process of HEVC. Usually, 7or 8 filtering is employed for MV signalling in the process of motion compensation in HEVC. The offset operation and scaling are employed in the process of signalling prediction which is predicted to be weighted prediction.

H.264/MPEG-4AVC accepts only 8 directional modes where as HEVC allows 33 directional modes [14-20]. The reference data will be considered from the nearby blocks where it

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is decoded by samples from the boundary of the image. In the process of quantization uniform quantization is employed with different scaling matrices by using the complete transformed block size. Context adaptive binary arithmetic coding (CABAC) is modified and used for entropy encoding to minimize the context memory requirements, to increase the throughput speed and to increase compression performance. The main objective is to rebuild the signal amplitudes that can be predictedbased on the histogram analysis near tothe encoder.

3. Encoding and Holoentropy Encoding

HEVC uses one entropy coding which is known as CABAC. Fig 2 illustrating the CABAC block diagram. Context modelling has been employed to enhance the efficiency of the CABAC. The indices of the context model are derived based on the splitting depth of the transform tree. The syntax elements of the indices are given as cfb_cb, skip_flag, unit_flag, cbf_luma, split_transform_flag and cbf_cr. Throughput of the CABAC could be estimated according to the number of bins are processed per second [21-25]. By varying binarization, eliminating redundant bins and interfering bin values total count of bins could be reduced. Pre-process of standardization block-based HEVC approach is used in HEVC [25-30]. Several numbers of improvements are prepared for framing an HEVC technique. HEVC coding technique includes changing the picture into coding tree units, PUs and PBs, dividing CTB into CB, partitioning of tree structure into units and transforming blocks, tiles and slice, inter-picture prediction, intra-picture prediction. Scaling and quantization, transform, in loop filters, entropy coding and special coding modes. HEVC separates colour video signals into three components and the model is named as YCbCr [31-34]. Whereas Cb represents grey colour deviation towards blue colour whereas Cr represents grey colour deviation towards red colour.

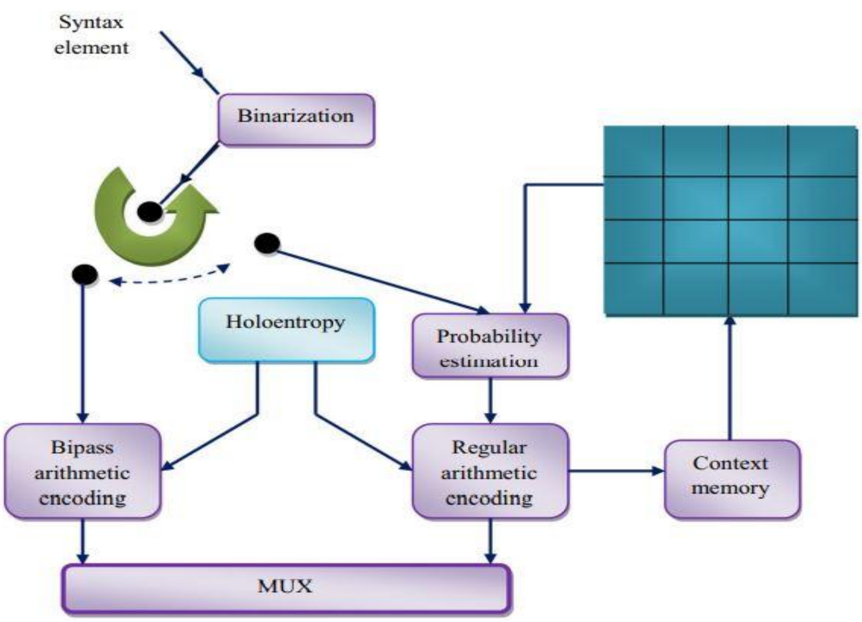

Fig 2. CABAC Block Diagram

3.1. Proposed Holoentropy:

Holoentropy $HE_x(z)$is defined as the sum of total correlation of the random vector Z and all entropies and it is expressed as equation 1. In this paper a novel optimization technique

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has been proposing for tuning correlation through a nonlinear relationship operator.

$HE_x(z) = H_x(z) + C_x(z) = \sum_{i=1}^{m} H_x(z_i)$ (1)

Where $HE_x(z)$ is the model of holoentropy, Z is the mutual information of discrete random vectors and m represents sum of attributes. Entropyrepresented as $H_x(z)$ and the correlation is expressed as $C_x(z)$ and $z_i$is the attributes of the categorical. Weighted holoentropy is expressed as equation 2, where it is equal to the sum of all total weighted entropies of random vector Z.

$$W_x(Z) = \sum_{i=1}^{m} W_x(z_i) H_x(z_i) \quad (2)$$

Where $W_x(z_i)$ represents the weighted tansig functionfor i =1,2……K.

$H_x(z_i)$ represents the i^{th}value of the holoentropy

A nonlinear relationship operator is employed for correlation function instead statistical correlation function.

$$W_x(z_i) = 2\left(1 - \frac{1}{1+e^{(-H_x(z_i))}}\right) \quad (3)$$

It is well known term that is Peak Signal to noise Ratio (PSNR) is considering as the measurement parameter. PSNR is also used as a measurement parameter for quality assessment between the compressed image and original image. The higher PSNR value indicates the better quality of reconstructed or the compressed image. The PSNR block calculates the PSNR value in terms dbs (Decibles) among the two images. In equation 4 the value of v = 1,2…K_v. Where $K_v$it represents the total count of video sequences. MSE_vgives the mean square error between reconstructed video sequence and the original video sequence and MAX_l gives the maximum value of the pixel in the image.

$$PSNR = \frac{1}{K_v}\sum_{v=1}^{K_v} 10\log_{10}\left(\frac{MAX_l^{\,2}}{MSE_v}\right) \quad (4)$$

In this regard the proposed technique is factorizing the weighted function $W_x(z_i)$ with $\beta_i$and it is represented as

$$W_x(z_i) = \beta_i\, 2\left(1 - \frac{1}{1+e^{(-H_x(z_i))}}\right) \quad (5)$$

Meanwhile the value of β_i will be optimally tuned based on Hybrid Grey Wolf Optimization (HGWO) technique. To reduce the search space in original Grey wolf optimization Genetic Algorithm has been is usedtherefore the resulting algorithm is named as Hybrid Grey Wolf Optimization.

Traditionally, GWO computes based on the social activities of grey wolves such as leadership and hunting hierarchy [6-10]. The grey wolves are classified as 4 general categories such as alpha, beta, delta, and omega $\alpha, \beta, \delta,$ and ω respectively as mentioned above to compute the GWO hierarchy (similar to the natural process). Moreover, it includes hunting, encircling, as well as attacking the prey, which are the three prominent stages in exploration and exploitation process of GWO for improving the efficiency of the algorithm. The wolves viz., $\alpha, \beta,$ and δ are assumed to be the prime wolves, which handle the hunting process. Among all those wolves, alpha wolves play the leader role and determine the activities related to the hunting behaviours, locations to sleep and awakening time, etc. Moreover, the alpha wolves decisiveness are commanded to the entire group yet, some of the independent activities are allowed in the group. Apart from the alpha wolves, beta and delta wolves occupy the 2nd and 3rd places correspondingly. Besides, β wolves support αfor the formulation of decisions regarding the pack activities and all wolves in the group. Along with these wolves, delta wolves are ranked as 3rd order wolves that should obey to alpha and beta wolves. Still, delta δ wolves can control the omega ω wolves. In addition to this, ω (omega) wolves take the last order in the group, which should obey all other wolves in the group. Furthermore, omega wolves are not directly involving in the hunting process, still they help to satisfy all other wolves in the group. Usually, these wolves (ω) are involved only for eating and acts as a caretaker for the entire group. Eq. (6) and Eq. (7) signifies the encircling activities of the wolves in the group, in which U and V signifies the coefficient vectors, $o_r(T)$represents the current iteration and $o(T)$refers to the grey wolves' position vectors.

$$Q = |U.o_r(T) - o(T)| \quad (6)$$

$$o_r(T+1) = o_r(T) - U.Q \quad (7)$$

Moreover, Eq. (4.18) and Eq. (4.19) demonstrates the creation of U and V in order, in which $a_i$points to a variable, which can be diminished constantly from 2 to 0 for all iterations. In addition, z_1 and z_2 refers to the arbitrary vectors which are ranges among [0, 1] persistently. Herein, the value of a_i ranges among 2 to 0, leads to generate low convergence, poor local searching capability, and minimum solving precision. Thus, the value of a_{ie} is subjected to diverse for all wolves as stated in Eq. (4.20) whereT specifies the current iteration and T_{max} points to the maximum iteration, and $Fit(Cs)$specifies fitness function of current solution. Further, the values of$U$ wolves are also differing for all wolves which lies among 1 to 3 representing α, βand δ as reffered in Eq. (4.18).

$$U_{ie} = 2ai_{ie}.z_1 - ai_{ie} \; ie = 1,2, \text{and } 3 \text{for } \alpha, \beta, \text{and } \delta \quad (8)$$

$$V = 2z_2 \quad (9)$$

$$ai_{ie} = 2(1 - \frac{T}{T_{max}}) \quad (10)$$

Eq. (4.21) to Eq. (4.27) exhibits the mathematical illustration of hunting activities of grey wolves, in which the Eq. (4.27) demonstrates the last adopted position of wolves with the updated $O_c$and ai. Algorithm 1 presents the pseudo code of proposed AGWO Algorithm-based filter coefficient optimization. Fig.4.4 represents the flowchart of proposed model.

$$Q_\alpha = |V_1 o_\alpha - o| \quad (11)$$

$$Q_\beta = |V_2 o_\beta - o| \quad (12)$$

$$Q_\delta = |V_3 o_\delta - o| \quad (13)$$

$$o_1 = o_\alpha - U_1.(Q_\alpha) \quad (14)$$

$$o_2 = o_\beta - U_2.(Q_\beta) \quad (15)$$

$$o_3 = o_\delta - U_3.(Q_\delta) \quad (16)$$

$$O_c(T+1) = \frac{o_1+o_2+o_3}{3} (17)$$

Eventually, the optimal position of the grey wolf which is referred as the updated $O_c$and a_{ie} is considered as the best position. Fig 3 represents the proposed Hybrid Grey Wolf Optimization algorithm.

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Input: m_c
Output: $m_c(t+1)$
Assign the grey wolves' population size
Allocate X, Y, UB, LB and t_{max}
Generate the initial positions of grey wolves with UB and LB
Initialize a, X and Y
Evaluate the fitness of the entire search agents
Allocate m_α as the best search agent
Allocate m_β as the second-best search agent
Allocate m_δ as the third best search agent
While($t < t_{max}$)
	For each search agent Update the position of the current search agent
	End for
	Update a, X and Y
	Calculate the fitness of search agents using GA
	Update m_α, m_β and m_δ
	$t = t + 1$
	End while
	Return m_α

Fig.3. Hybrid GWO optimization Algorithm

Results and discussions

Simulation procedure

The proposed holoentropy encoding based on HEVC through HGWO was implemented in JAVA. YUV file is used as data set for this proposed work such as tennis, foreman, coastguard, mobile, football and garden with corresponding count of sequences as 300, 300, 112, 115, 125 and 140. The performance of the proposed method is measured over existing optimization algorithms in terms of SSIM, UQI, RMSE and Bit Rate.

Result Analysis

In terms of SSIM:

For tennis image the proposed algorithm is enhanced the encoding performance as 0.30%, 1.40 & 2.60% over GWO,FF and ABC optimization algorithms. For mobile image the proposed algorithm is enhanced the encoding performance as 0.30%, 1.40 & 2.60% over GWO, FF and ABC optimization algorithms. For foreman image the proposed algorithm is enhanced the encoding performance as 0.20%, over GWO optimization algorithm. The performance of the proposed method over existing optimization algorithms in terms of SSIM is represented graphically in fig 4.

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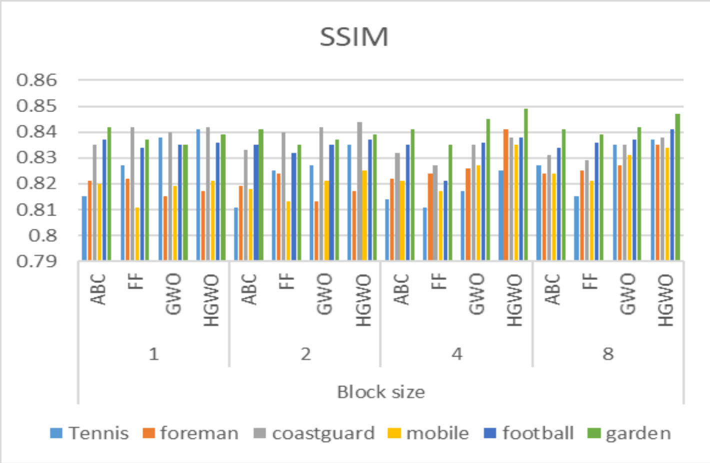

Fig 4 Graphical representation of proposed method in terms of SSIM

In terms of UQI:

For tennis image the proposed algorithm is enhanced the encoding performance as 0.20%, 1.1&0.60% over GWO, FF and ABC optimization algorithms. For foreman image the proposed algorithm is enhanced the encoding performance as 0.20%, 0.40 &0.60% over GWO, FF and ABC optimization algorithms. For coast guard image the proposed algorithm is enhanced the encoding performance as 0.30%, 0.40 &0.60% over GWO, FF and ABC optimization algorithms. For mobile image the proposed algorithm is enhanced the encoding performance as 0.50%, 1.10%& 1.2% over GWO, FF and ABC optimization algorithms. For football image the proposed algorithm is enhanced the encoding performance as 0.1%, 0.7& 0.5% over GWO, FF and ABC optimization algorithms. For garden image the proposed algorithm is enhanced the encoding performance as 0.8%, 1.4%&1.5% over GWO, FF and ABC optimization algorithms. The performance of the proposed method over existing optimization algorithms in terms of UQI is represented graphically in fig 5.

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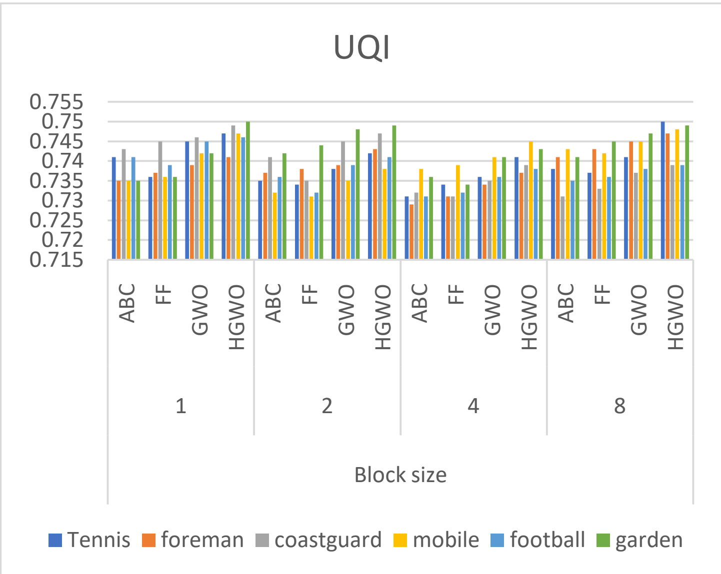

Fig 5 Graphical representation of proposed method in terms of UQI

In terms of RMSE:

For tennis image the proposed algorithm is improved the encoding performance by reducing mean

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square error as 0.4%, 1.2%&1.0% over GWO, FF and ABC optimization algorithms. For foreman image the proposed algorithm is enhanced the encoding performance by reducing mean square error as 0.40%, 0.70 & 0.60% over GWO, FF and ABC optimization algorithms. For coast guard image the proposed algorithm is enhanced the encoding performance by reducing mean square error as 0.4%, 1.7%&1.8% over GWO, FF and ABC optimization algorithms. For mobile image the proposed algorithm is enhanced the encoding performance as 0.50%, 0.70% & 1.0% over GWO, FF and ABC optimization algorithms. For football image the proposed algorithm is enhanced the encoding performance by reducing mean square error as 0.4%, 0.6%& 0.7% over GWO, FF and ABC optimization algorithms. For garden image the proposed algorithm is enhanced the encoding performance by reducing mean square error as 0.2%, 0.7% &0.9% over GWO, FF and ABC optimization algorithms. The performance of the proposed method over existing optimization algorithms in terms of RMSE is represented graphically in fig 6.

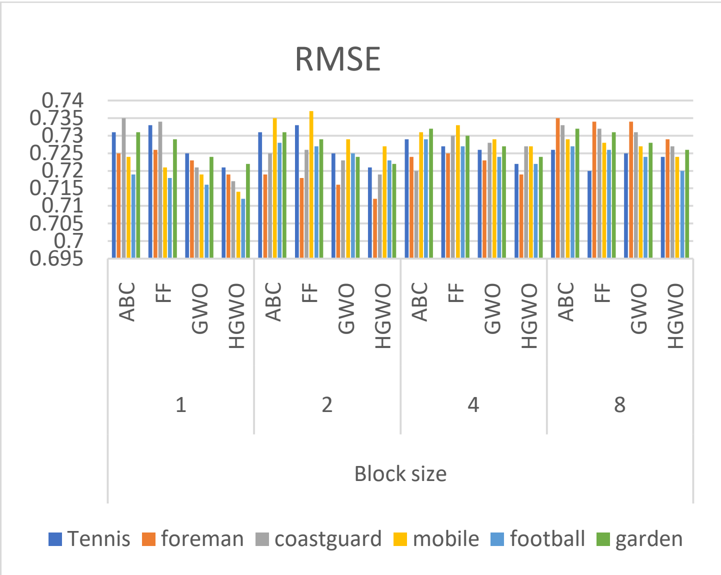

Fig 6 Graphical representation of proposed method in terms of RMSE

In terms of Bit Rate:

For tennis image the proposed algorithm is enhanced the encoding performance as 2%, 4% over GWO and ABC optimization algorithms. For foreman image the proposed algorithm is enhanced the encoding performance as 2%, 5% over GWO and ABC optimization algorithms. For coast guard image the proposed algorithm is enhanced the encoding performance as 2%, 4% over GWO and ABC optimization algorithms. For mobile image the proposed algorithm is enhanced the encoding performance as1% &3% over GWOand ABC optimization algorithms. For football image the proposed algorithm is enhanced the encoding performance as 3%, 5%over GWO and ABC optimization algorithms. For garden image the proposed algorithm is enhanced the encoding performance as 3%, 7%over GWOand ABC optimization algorithms. The performance of the proposed method over existing optimization algorithms in terms of Bit Rtae is represented graphically in fig 7.

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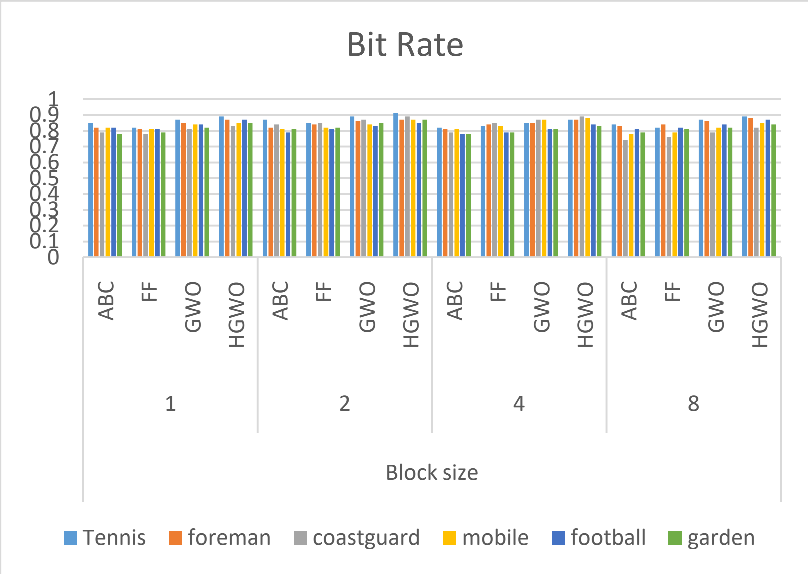

Fig 7 Graphical representation of proposed method in terms of Bit Rate

Conclusion

In this paper a new encoding process is implemented in HEVC based on enhanced holoentropy for efficient compression. In this regard, the encoding in the HEVC system was obtained by enhanced holoentropy that was determined based on weighting tansig function. consequently, the weights of tansig function were optimally tuned through the Hybrid Grey Wolf Optimization Algorithm. When high-resolution video sequences were processed, it needs considerable development. The pixel deviations beneath altering frames were clustered depending on the interest, and accordingly, the outliers were eliminated using a sophisticated entropy standard known as enhanced holoentropy. Moreover, the adopted approach was distinguished with the traditional techniques namely ABC, FF and GWO in terms of SSIM,RMSE, bit rate and UQI, From the result analysis, for block size 1, the proposed algorithm has attained better results over existing optimization algorithms which was analysed in results and discussions section.

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