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DYNAMIC QUANTILE MULTIOBJECTIVE DRAGONFLY OPTIMIZED HEVC USING MULTI-CORE DSPFOR ROBUST MULTIMEDIA COMMUNICATION

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ABSTRACT

Revolutions in communication systems are increasing extensively. As far as multimedia communication systems are concerned, technology has shifted from analog television to digital television. Owing to the extensive applications of users, data compression are said to be more significant to reduce system resources. Also, an increase in data size necessitates excessive transmission bandwidth. This navigates the advancements in compression and therefore the requirement of a new codec. Numerous algorithms are utilized in achieving image compression and are categorized in terms of codecs. Moreover, the employment of video compression technology like High Efficiency Video Coding (HEVC) minimizes the system resource utilization to name a few being memory utilization, bandwidth and processing time. This is feasible by minimizing the video codecs complexity without compromising on video quality output both in terms of time and computational efficiency. With this objective in this work a method called, Dynamic Quantile Regressive Multiobjective Dragonfly Optimization (DQRMDO) employing HEVC video encoder/decoder on 8 core DSP processors to ensure time and computational efficient robust multimedia communication is proposed. Dragonfly Optimizationin our work is used to optimize the coding unit partitioning pattern of CTU in HEVC video encoder/decoder. This is done by employing Quantile Regression analysis for identifying the fitness of all CU partitioning pattern on the basis of the multiple objectives. With this, optimal CU partitioning pattern in HEVC standard is identified to efficiently encode/decode the frames in the video images. This helps to achieve robust multimedia communication using multi-core DSP processor. Simulations are performed to analyze the DQRMDO method in terms of bandwidth, latency and throughput. The obtained results show that the DQRMDO method attained better performance than the conventional methods.

Keywords: High Efficiency Video Coding, Video Compression, Quantile Regression, Multiobjective Dragonfly Optimization, Multimedia Communication

1. INTRODUCTION

In the course of the past few years, the world of multimedia has observed an authentic insurgence through the arrival of a myriad of applications where digital videos are found to be ubiquitous. This insurgence is be associated by users' interest in intriguing and high quality video contents and by the plan of actions assisting video sharing concerning video streaming, messaging manifestos and so on. A hybrid HEVC encoder that integrates two distinct acceleration techniques on the basis of parallel computing and source code optimization was designed and developed in [1]. The first acceleration technique being a parallel model that employed a domain decomposition model on the basis of HEVC slice partitioning, that is specifically appropriate for making use of the shared memory parallelism of multi-core processors. On the other hand, the second acceleration technique employed optimization methods at CTU level with the purpose of minimizing the quad tree splitting procedure complexity by means of a CNN, therefore significantly reducing the intra coding time considerably. With the evolution of artificial intelligence (AI)-based multimedia numerous video-based services has been designed over the past few years for video surveillance with high definition (HD), ultra-high definition (UHD) and mobile multimedia streaming. However, these new services necessitate higher video quality to attain the objective of quality of experience (QoE) indispensable by the users.Wide-activated Squeeze and Excitation Deep Convolutional Neural Network (WSE-DCNN) was proposed in [2] to ensure video quality enhancement.With this type of design eliminated the requirement of compression artifacts therefore enhancing the visual quality and improving the overall end user QoE.

Nevertheless certain research works presumes to have information pertaining to the workload prior to decoding process itself. Some other does not employ contemporary asymmetry characteristics of mobile structure. To focus on this issue, a method based on classification and frequency scaling was proposed in [3]. Initially during design time classification of frames on the basis of type and size was modeled. Followed by which the decode process was structured and finally, selected frequency was fine tuned arbitrarily on the basis of output buffer size.HEVC extensively minimizes bit-rates upon comparison to the previous H.264 standard but at the expense of exceptionally elevated complexity involved in encoding. This is due to the reason that in HEVC, the quad-tree partition of coding unit (CU) is said to consume a proportionate amount of HEVC encoding complexity, owing to the optimization involved in rate distortion.In [4], a deep learning method for predicting CU partitioning for minimizing HEVC complexity involved at both intraand inter-modes, based on convolutional neural network (CNN) and long- and short-term memory (LSTM) network was proposed. Yet another method taking into considerations the spatial temporal complexity involved was presented in [5] on the basis of hierarchical LSTM that in turn reduced the computational time considerably.

Double compression detection is considered as one of the fundamental process while performing digital video integrity analysis. This is due to the reason that while performing digital video integrity analysis is considered to be the major aspects in video forensics. But, most of the prevailing methods are found to be highly susceptible with the severe lossy quantization and as a result are considered to be most demanding to acquire frame-wise detection results in a reliable manner. In [6], a hybrid neural network was designed to obtain abnormal frames in HEVC videos with double compression by means of robust spatial-temporal representations in the compression domain itself. As a result, bit rates was said to be improved considerably. A detailed search space analysis on HEVC was investigated in [7] and [8].Owing to the extensive evolution of both multi-medias and internet utilizations, significant video transmission via HEVC is considered to be the most major concerns. Also to transmit video stream in an efficient manner via internet video coding process is utilized that in turn compresses digitized video data. As the postulation of quantization matrix becomes a significant characteristic in prevailing video CODECs, an optimized quantization matrix is being contemplated in the HEVC standard.In [9], entropy encoding by acquainting optimized quantization matrix was presented that in turn ensured higher rate of compression upon comparison to the improved entropy encoding. Also, to circumvent attacks efficient embedding mechanism was designed in [10] that by employing stego-message ensured expectations of security in an extensive manner.

1.1 Contributions of the work

Taking into consideration the above performance metrics and to solve the above said issues, in this work a method called, Dynamic Quantile Regressive Multiobjective Dragonfly Optimization (DQRMDO) employing HEVC video encoder/decoder on 8 core DSP processors to ensure time and computational efficient robust multimedia communication is proposed. The essential contributions of DQRMDO are listed below,

- To improve the throughput rate for efficient robust multimedia communication, DQRMDO method is proposed. The DQRMDO method is introduced by applying the quantile regression based fitness function and multi-objective dragon fly optimization on contrary to existing work that used artificial intelligence technique.
- To improve the bandwidth and latency, multiple objective functions like rate distortion cost and energy consumption are utilized via Quantile Regression function. Also by employing this dynamic Quantile Regression functions permits in comprehending relationships between variables (i.e., RD cost and energy consumption).

- To improve the throughput factor, Dynamic Multiobjective Dragonfly Optimization algorithm is employed that uses three distinct processes, separation, alignment and cohesion on the basis of the prevailing frame positioning of an available CU at a definite time instance and the nearest frame positioning.
- The performance was evaluated through extensive simulations with short videos dataset and validated with the state-of-the-art methods.

1.2 Organization of the work

The rest of the paper is organized as follows: Section 2 describes certain prior methods and basic concepts related with HEVC using optimization techniques in combination with coding standards. Section 3 elaborates the proposed method, Dynamic Quantile Regressive Multiobjective Dragonfly Optimization (DQRMDO) employing HEVC video encoder/decoder on 8 core DSP processors. Section 4 elucidates the experimental setup followed by implementation details in Section 5. Section6 presents the performance metrics and the results that verify and validate the applicability and the robustness of the DQRMDO method. Finally, Section 7 gives the concluding remarks.

2. RELATED WORKS

In recent days, both video and multimedia content are exercising control over the Internet. The advantage of HEVC remains in boosting compression performance upon comparison to the prevailing standards and hence constitutes a paramount step as far as video compression technology is concerned. But the enhancement is said to be arrived at only by elevating the encoding complexity. In [10], an HEVC-adaptable mechanism with the purpose of both hiding and obtaining high resolution videos were obtained. This was ensured on the basis of enhancement of certain blocks via luminance. With this the video quality was said to be maintained in a considerable manner. A holistic review and challenges involved in the design of multimedia service delivery via continuous time varying quality models was designed in [11].Nevertheless, the prevailing rate control streamlines updates it parameters based on a predetermined initialization that in turn would result in certain types of prediction errors of bit allocation. To address on this issue, a learning-based mapping method was designed in [12] to arrive at an accurate and precise target bit rate and good video quality in an extensive manner. Good video coding quality for low-bitrate applications are considered to be the need of the hour as far as transmission of bandwidth in a narrow fashion and constrained capacity in terms of storage. HEVC, a mentioned earlier is considered to be the acceptable replacement as far as encoding ultra-high-definition video. Upon comparison to other prototypes, HEVC utilizes numerous coding mechanisms to discard redundancy present in inter and intra-frames.

An orthogonal frequency division multiplexing for multimedia wireless communication was presented in [13]. Here, block code employing rate less space time was employed to improve both bit error rate and PSNR significantly. Yet another method employing an adaptive down sampling-based coding model was designed in [14] with the purpose of enhancing the bit rate efficiency involved in compression of HEVC. This in turn resulted in maximum improvement in terms of both PSNR and bit rate significantly. Nevertheless, these mechanisms increased the complexity involved in the computational process particularly performed during the inter-prediction process. To improve the complexity an effective prediction mechanism for enhancing HEVC inter-coding was proposed in [15]. Here, a fast decision method was designed by taking into considerations the spatial association between the prevailing block and its adjacent block in the previous frame. With this the coding time was saved considerably.With the 5G network complexity and the multifarious necessitates for multimedia content and video transmission, in distinct channel environments good performance of digital media content transmission is considered to be one of the major challenges to be addressed. On the basis of the code stream structure features of screen content in HEVC, a joint source channel coding (JSCC) method to analyze and validate compressed video transmission in wireless channels was presented in [16]. Yet another dragonfly optimization method to minimize overhead and ensure high quality video was proposed in [17].

However, the methods discussed above are said to be applied externally on confident users or computers, and there has been a dearth of similar methods that can be efficiently performed via an un-trusted transmission medium. In [18], a self-embedding-based High-Efficiency Video Coding (HEVC) transmission and integrity verification method was proposed to ensure high protection and robust multimedia communication. Yet another optimized allocation method employing frame level bit allocation was presented in [19] to not only improve bit rate accuracy but also enhance the PSNR rate in a significant manner. Yet another method to minimize the complexity involved in encoding without minimizing the video conferencing quality was designed in [20].

Here we present an improved optimization method for robust multimedia communication using multi-core DSP called, Dynamic Quantile Regressive Multiobjective Dragonfly Optimization (DQRMDO) using short videos dataset. The proposed dynamic Dragonfly Optimization optimized the coding unit partitioning pattern of CTU in HEVC video encoder/decoder. Quantile Regression analysis on the other hand identifies the fitness of all CU partitioning pattern on the basis of the multiple objective (i.e., minimal rate distortion cost and energy consumption). The DQRMDO method results of the optimization for melanoma using short videos dataset are compared with the state-of-the-art methods for validation.

3. METHODOLOGY

In this section, robust multimedia communication using HEVC standard on 8 core DSP processors called, Dynamic Quantile Regressive Multiobjective Dragonfly Optimization (DQRMDO) is proposed. The DQRMDO method applies Dragonfly Optimization algorithm to determine the optimal CU partitioning patterns in CTU by measuring RD cost. With this, fast multimedia communication is ensured. Figure 1 shows the structure of Dynamic Quantile Regressive Multiobjective Dragonfly Optimization (DQRMDO) method.

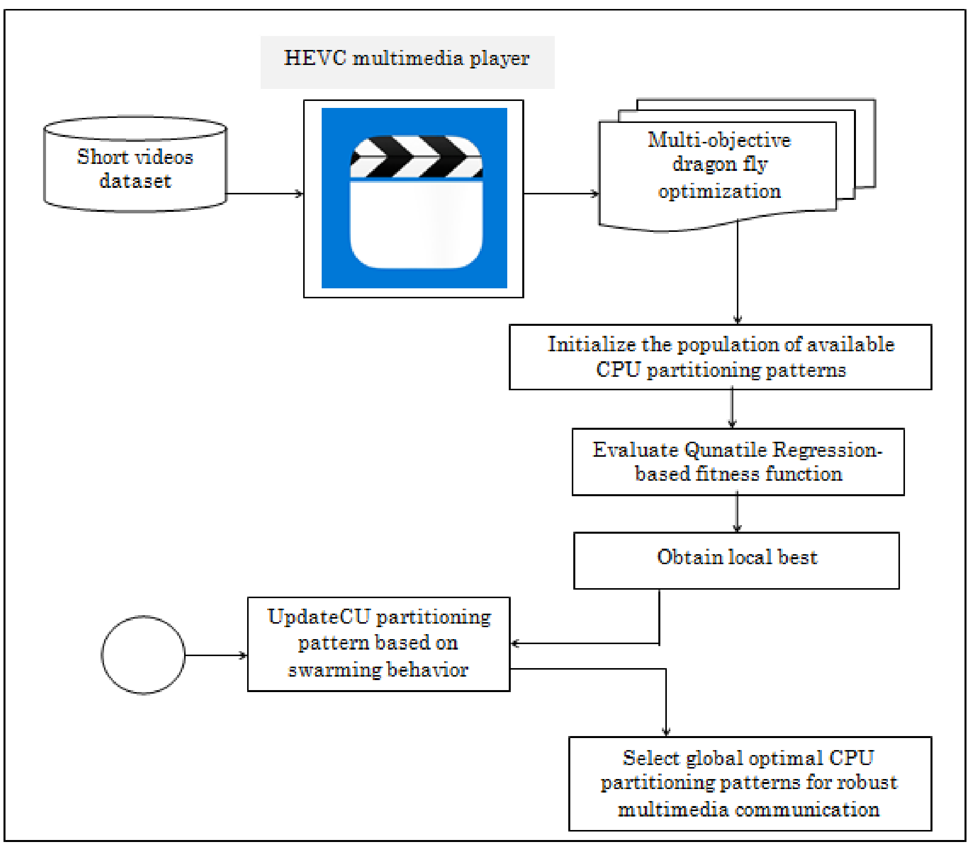

Figure 1 Structure of Dynamic Quantile Regressive Multiobjective Dragonfly Optimization (DQRMDO)

As illustrated in the above figure, the proposed DQRMDO method for HEVC video encoder/decoder on 8 core DSP processors different numbers of videos are acquired from short videos dataset https://www.kaggle.com/datasets/mistag/short-videosand are provided as input. The proposed DQRMDO method initializes the populations of dragonflies (i.e., CU partitioning pattern) in the search space. Followed by which for each initialized population, proposed dragonfly optimization determines optimal CU partitioning pattern by means of computing multiple objective functions. Next, the proposed DQRMDO method performs Quantile Regression analysis to identify the fitness of all CU partitioning pattern based on multiple objective functions. Here, multiple objective functions considered are minimum Rate Distortion cost (RD cost) and Energy Consumption (EC). From this, the best fittest CU partitioning pattern among the population is identified. Finally, global optimal solution among population is determined to identify the optimal CU partitioning pattern of each CTU in HEVC. With this, reliable multimedia communication is said to be arrived at employing DQRMDO.

3.1 DQRMDOSystem model

As introduced before HEVC reinforces hierarchical block partitioning it is said to be modeled using quadtree-based block partitioning construction. Three kinds of units are involved in the quadtree-based block partitioning structure. They are, Coding Unit (CU), Prediction Unit (PU) and Transform Unit (TU). Figure 2 shows the system model of DQRMDO.

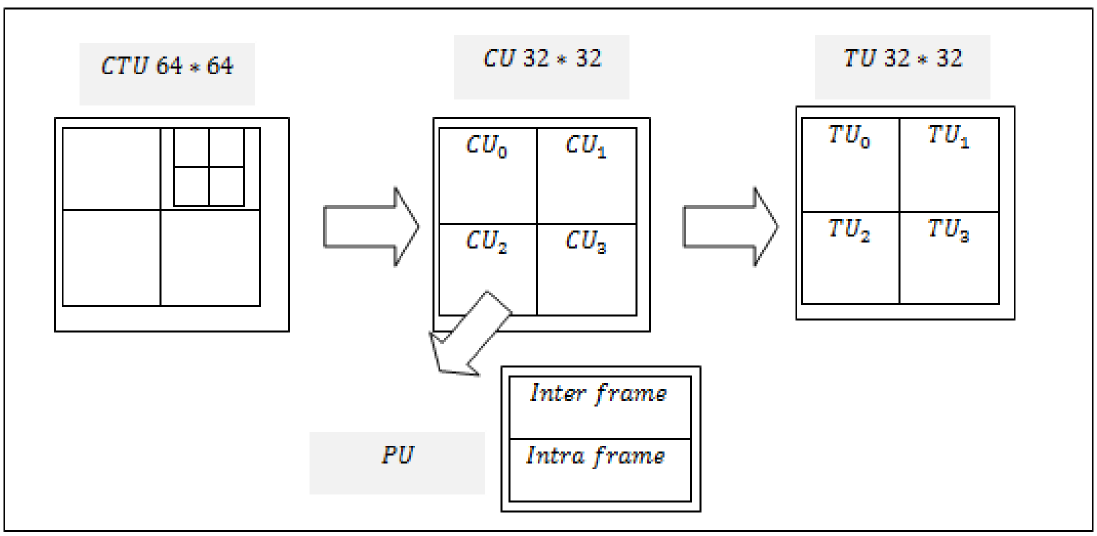

Figure 2 System model of DQRMDO

As illustrated in the above figure, the largest CU is referred to as a Coding Tree Unit (CTU) that is also employed as the root of a coding quadtree. Each CTU can be further split into smaller CUs in accordance with the quadtree structure. As noted the CU size differs from CTU (64*64 pixels) to the smallest CU (8*8 pixels). In addition, each CU in certain case also serves as the root of another quadtree and is referred to as Residual Quad Tree (RQT). A CU is also split into Partitioning Units (PU) and also each leaf of the RQT is referred to as TU (32*32 pixels to 4*4 pixels). The above quadtree partitioning structure though significantly enhances the HEVC coding performance, but needs to be performed a comprehensive search over all probable partitioning candidates of CUs, PUs, and TUs to identify the best and global one. In this work, Dynamic Quantile Regressive Multiobjective Dragonfly Optimization method is designed to achieve the above objective.

3.2 Dynamic Quantile Regressive Multiobjective Dragonfly Optimization

In this section a Dynamic Quantile Regressive Multiobjective Dragonfly Optimization method for robust multimedia communication is proposed. The input videos obtained from short video dataset are converted into frames or images.

The images or frames in this work are referred as a basic processing unit or Coding Tree Unit (CTU). As illustrated in the above system model, the CTU HEVC splits the image or frames into different Coding Units (CU) and then into distinct prediction units (PUs) and finally into transform units (TUs). To obtain an optimal CU partitioning pattern, optimization of HEVC encoder is perform therefore ensuring reliable multimedia communication.

Let us consider CU partitioning pattern consisting of 'n' CU patterns with the available partition patterns in HEVC identified as '$CU = CU_1, CU_2, \ldots, CU_n$'. The proposed multiple objectives Dynamic Quantile Regressive Multiobjective Dragonfly Optimization are categorized as a meta-heuristic model that is applied to identify the solution of an optimization problem. In DQRMDO, the multiple objectives include minimum rate distortion cost and minimum energy consumption.On comparison to the traditional methods, the newly developed method uses a Quantile Regression analysis model for identifying the global best result within the population in the search space in a shorter period of time (i.e., encoding/decoding) with improved PSNR and bit rate. By using the Dynamic Quantile Regressive Multiobjective Dragonfly Optimization algorithm, such parameters as PSNR, bit rate, convergence speed (i.e., encoding/decoding time) are improved.

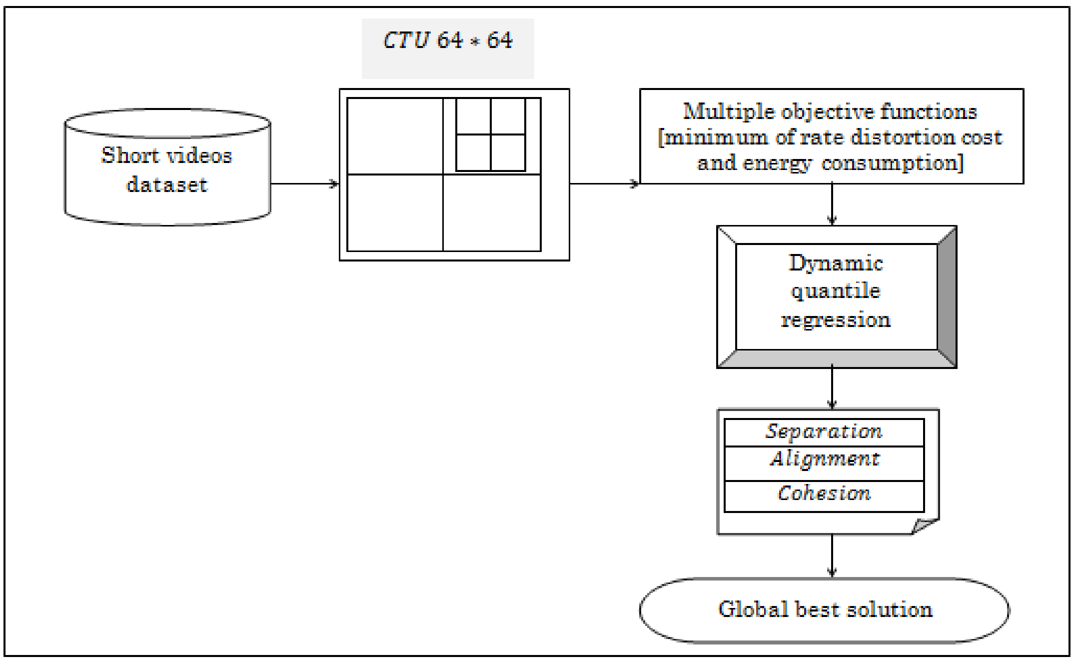

Figure 3 Block diagram of Dynamic Quantile Regressive Multiobjective Dragonfly Optimization for robust multimedia communication (figure modified)

As shown in the above figure, in the proposed DQRMDO method sample video obtained from short videos dataset is subjected to multiple objective functions, i.e.rate distortion cost and energy consumption. Followed by which dynamic quantile regression function is applied for associating relationships between the multiple objective functions and return the results accordingly. Finally, the obtained results are modeled using three stage process of swarming behaviors, namely, separation, alignment and cohesion to generate global best solution.With this end, in the proposed DQRMDO method the population of dragonflies (i.e. available CUs) is initialized and the dragonflies move within the search space.To start the optimization procedure, the CU population prevailing in the search space is first initialized and is mathematically stated as given below.

$$CP = \{CU_1, CU_2, \dots., CU_n\} \quad (1)$$

From the above equation (1), 'CP' represent the current population of the available coding units '$CU_1, CU_2, \dots., CU_n$'. Moreover, to obtain the global best solution, the proposed method creates a dynamic Quantile Regression function from the current population. The purpose of using this dynamic Quantile Regression function in our work is that it allows for comprehending relationships between variables (i.e., RD cost and energy consumption) outside of the mean of data. Moreover, it is also useful in comprehending the output results of CUs that have nonlinear correlation so that the top 10% CUs can now be diversely correlated from the bottom 10% CUswhile ensuring robust multimedia communication in a computationally efficient manner. This is mathematically formulated as given below.

$$\log(MOF_i) = \alpha_{(\tau)*} + \beta_{(\tau)*} RDCost_i(P) + \gamma EC_i(P) \quad (2)$$

From the above equation (2), 'τ' represent the quantile level of the fitness of all the CU partitioning pattern. Upon successful completion of the population generation process, the objective function is obtained for each dragonfly (i.e. CU) according to the abovementioned multiple objective functions. For this purpose, the CU is classified according to the quantile levels of the video coding parameters (i.e., minimum rate distortion cost 'RDC' and energy consumption 'EC') and examined whether the CUs belonging to each quantile level act correctly from the point of view of the hypothesized theory or not.Moreover, we also additionally investigated which quantile level of CUs is more vehemently contributed by hypothesized theory based on two videos coding parameters for obtaining global optimal solution in an extensive manner. For this purpose, initially, the Rate Distortion cost for each CU is calculated as given below.

$$\min_{P \in CU} \sum_{i=1}^{n} CD_i(P), such that \sum_{i=1}^{n} CB_i(P) \leq CB, \sum_{i=1}^{n} ACC_i(P) \leq ACC \quad (3)$$

From the above equation (3), the rate distortion cost is measured by taking into considerations the coding distortion rate 'CD_i', coding bits 'CB_i', assigned computational complexity 'ACC_i'for coding unit parameter set 'P' of '$i-th$' unit with respect to total number of CU units 'n' respectively. By introducing the Lagrangian Relaxation multiplier 'λ' and splitting the constraints in 'ACC' such that '$ACC_1(P) \in R^{m_1,n}$,$ACC_2(P) \in R^{m_2,n}$' then, the constrained optimization problem in equation (3) is converted as given below.

$$\min_{P \in CU} \sum_{i=1}^{n} RDCost_i(P) = CD_i(P) + \lambda^T CB_i(P) \quad (4)$$

Following which to measure the video encoder/decoder performance under energy constraints, the average video encoder/decoder distortion measure are evaluated as given below.

$$\mu(Dist_{Enc}) = \frac{\sum_{i=1}^{CF} Dist_{Enc}^{i} + (CF-EF)Dist_{max}}{CF} \quad (5)$$

$$\mu(Dist_{Dec}) = \frac{\sum_{i=1}^{CF} Dist_{Dec}^{i} + (CF-EF)Dist_{max}}{CF} \quad (6)$$

$$EC = \mu(Dist_{Enc}) + \mu(Dist_{Dec}) \quad (7)$$

From the above equations (5) and (6), the average video encoder '$\mu(Dis_{Enc})$' and average video decoder '$\mu(Dis_{Dec})$' is measured by taking into considerations the total number of frames in current CU 'CF', number of frames encoded 'EF' with respect to the maximum distortion '$Dist_{max}$' of a video frame obtained for simulation. Finally the energy consumption rate is obtained from equation (7). Depending on the above measure metrics, i.e., rate distortion and video encoder/decoder performance under energy constraints, fitness function is measured as given below.

$$\alpha_{FF} = \{RDCost_i(P), EC\} \quad (8)$$

From the above equation (8), 'α_{FF}' refers to the minimum rate distortion cost and the minimal average video encoder and decoder under energy constraints. With the above fitness value determined, the CUs of each sample videos 'SV' are integrated into one and the CUs are sorted according to the fitness value result. The CU with minimum '$RDCost_i(P)$' and 'EC' is arranged first and on contrary the maximum value are arranged last.

$$CU = \alpha_{FF}(CU_1) > \alpha_{FF}(CU_2) > \cdots > \alpha_{FF}(CU_n) \quad (9)$$

With this, 'n' best available CUs are selected to obtain the global best solution. According to the fitness function as measured in equation (8), the global best CU in the search space is estimated by means of four distinct processes, separation, alignment, cohesion, and attraction towards the efficient multimedia communication. To start with the separation procedure, the current the current frame positioning of the sample video CU and its nearest frame positioning is measured as given below.

$$Sep = \sum_{j=1}^{m} CPosCU(t) - CPosCU_j(t) \quad (10)$$

From the above equation (10) the results of separation process 'Sep' is obtained based on the current frame positioning of an available CU at time 't', '$CPosCU(t)$' and the nearest frame positioning at time 't', '$CPosCU_j(t)$' and 'm' represents the number of nearest CUs.

Followed by which velocity of the CUs (i.e., frames magnitude and direction) is measured and the nearest congruent process is done in the alignment procedure. This alignment procedure is mathematically stated as given below.

$$Align = \sum_{j=1}^{m} \frac{Vel_j(t)}{m} \quad (11)$$

From the above equation (11), the alignment procedure is performed '$Vel_j(t)$' according to the velocity (i.e., in terms of magnitude and direction) of nearest CUs at time 't' with respect to the number of nearest CUs 'm' respectively. The third procedure is referred to as cohesion. With the basic principle that the CUs be inclined to travel to the center point of processing units (i.e., in terms of inter frame/ intra frame). This cohesion procedure is mathematically represented as given below.

$$Cohes = \sum_{j=1}^{m} \frac{CPosCU_j(t) - CPosCU(t)}{m} \quad (12)$$

From the above equation (12), cohesion of the CU '$Cohes$' is measured by taking into consideration, nearest frame positioning at time 't', '$CPosCU_j(t)$' and current frame positioning of an available CU at time 't', '$CPosCU(t)$' respectively. Finally, the frame positioning of the CU gets updated to obtain the global best solution. This is mathematically formulated as given below.

$$CPosCU_j(t+1) = CPosCU_j(t) * \Delta CPosCU_j(t+1) \quad (13)$$

$$\Delta CPosCU_j(t+1) = \{W_1(Sep) + W_2(Align) + W_3(Cohes)\}.\, CPosCU_j(t) \quad (14)$$

From the above equations (13) and (14), step vector for locating the signal direction of the CU is obtained '$\Delta CPosCU_j(t+1)$' based on the weight of separation '$W_1(Sep)$', weight of alignment '$W_2(Align)$', weight of cohesion '$W_3(Cohes)$' and the current frame positioning '$CPosCU_j(t)$' respectively. With this optimal CU partitioning pattern of each CTU in HEVC is identified in a significant and robust manner. The pseudo code representation of Dynamic Quantile Regressive Multiobjective Dragonfly Optimizer is given below.

Input: Dataset 'DS', Sample Videos '$SV = \{SV_1, SV_2, \ldots, SV_N\}$'
Output: robust multimedia communication
Step 1: **Initialize** 'N', 'n', Lagrangian Relaxation multiplier '$\lambda = 0.5$', total number of frames in current CU 'CF', number of frames encoded 'EF', allowed maximum distortion '$Dist_{max}$' Step 2: **Initialize** coding distortion rate 'CD_i', coding bits 'CB_i', assigned computational complexity 'ACC_i' Step 3: **Begin** Ste 4: **For** each Dataset 'DS' with Sample Videos 'SV' Step 5: Initialize CU population as given in equation (1) Step 6: Evaluate dynamic Quantile Regression function to obtain global best solution as given in equation (2) Step 7: Evaluate Rate Distortion cost for each CU as given in equations (3) and (4) Step 8: Measure video encoder/decoder performance under energy constraints as given in equations (5) and (6) Step 9: Measure overall energy consumption as given in equation (7) Step 10: Evaluate fitness function as given in equation (8) **//Separation process** Step 11: Perform separation procedure as given in equation (10) **//Alignment process** Step 12: Perform alignment procedure as given in equation (11) **//Cohesion process** Step 13: Perform cohesion procedure as given in equation (12) **//Global best solution** Ste 14: Obtain global best solution as given in equations (13) and (14) Step 15: **End for** Step 16: **End**

Algorithm 1 Dynamic Quantile Regressive Multiobjective Dragonfly Optimizer

As given in the above algorithm with the objective of ensuring robust (i.e., withstanding different types of deliberate or unexpected disturbances) multimedia communication. With this objective, a dynamic and multi-objective dragonfly optimizer model with multi-objective being satisfied by means of quantile regression function is designed. First, with the sample videos in the form of videos obtained from the input dataset, CU population is initialized to perform the process. Second, dynamic Quantile Regression function is formulated to obtain global best solution. Followed by which, rate distortion cost and energy consumption is evaluated to obtain the fitness function. Next, the three different processes, separation, alignment and cohesion is applied based on the current frame positioning of an available CU at a definite time instance and the nearest frame positioning respectively. Finally, the global optimal solution among population is evaluated to identify the optimal CU partitioning pattern of each CTU in HEVC.

4. EXPERIMENTAL SETUP

In this work, DSP (Digital Signal Processors) Simulink MATLAB software is utilized to validate the robust multimedia communication performance of proposed optimization method of HEVC using Multi-Core DSP. In Simulink, the DSP System Toolbox provides with a library of signal processing algorithm blocks and with these blocks process streaming input signals as individual samples or as collections of samples referred to as frames. Moreover to ensure low latency and high throughput, the system toolbox maintains both sample-based and frame-based processing modes. Also to provide fair comparison between the proposed Dynamic Quantile Regressive Multiobjective Dragonfly Optimization (DQRMDO) employing HEVC video encoder/decoder on 8 core DSP processors and existing methods, hybrid HEVC encoder [1] and Wide-activated Squeeze and Excitation Deep Convolutional Neural Network (WSE-DCNN) [2], short videos dataset obtained from https://www.kaggle.com/datasets/mistag/short-videosis provided as input. Simulations are performed with the purpose of validating the proposed DQRMDO method in terms of performance metrics like, bandwidth, latency and throughput with existing conventional methods, hybrid HEVC encoder [1] and WSE-DCNN [2] respectively.

5. IMPLEMENTATION DETAILS

In this study we developed an optimization method for robust multimedia communication called, Dynamic Quantile Regressive Multiobjective Dragonfly Optimization (DQRMDO) employing HEVC video encoder/decoder on 8 core DSP processors with low latency, bandwidth and improved throughput.

- The DQRMDO method comprises of two sections, namely, future signal quality prediction and optimal handover process.
- The DQRMDO method is compared with two existing methods, hybrid HEVC encoder [1] and WSE-DCNN [2] using short videos dataset to validate the results.
- Initially, the short videos were obtained from the input dataset.
- In the first part, Dynamic Quantile Regressive Multiobjective Dragonfly Optimization model is initially subjected to multiple objective functions, i.e., minimizing rate distortion cost and energy consumption using Dynamic Quantile Regression function, therefore ensuring local best solution. Next, with the employed fitness function, are sorted according to the fitness value result.
- Second, with the obtained local best results, the CUs are subjected to swarm or flocking behaviors by separately applying separation, alignment and cohesion to arrive at the global optimal solution for robust multimedia communication.According to the above implementation patterns, three different evaluation metrics, namely, bandwidth, latency and throughput are detailed in the next section.

6. DISCUSSION

6.1 Performance analysis of bandwidth and latency

In this section the bandwidth involved in robust multimedia communication is detailed. Bandwidth refers to the capacity at which a network can transmit data. In our work the data is in the form of sample video. To calculate the bandwidth for sample video streaming, the video duration should be multiplied by the data transmitted per second. The bandwidth rate is mathematically evaluated as given below.

$$BW = Dur(Video) * DTPS \quad (15)$$

From the above equation (15), bandwidth 'BW' is measured by taking into consideration the duration of video taken for sample simulation '$Dur(Video)$' and the data transmission involved for each sample video '$DTPS$' respectively. It is measured in terms of bits per second (Bps). Latency on the other hand is measured by taking into considerations the sum of all probable delays a video can face during multimedia transmission. Based on the networks and applications in use, the acceptable network latency results differ. For example in our work, video streaming should possess low network latency in order to work in an efficient manner.

$$Lat = Delay_P + Delay_T + Delay_{Propag} + Delay_Q \quad (16)$$

From the above equation (16), latency 'Lat' is measured by taking into considerations the processing delay '$Delay_P$', transmission delay '$Delay_T$', propagation delay '$Delay_{Propag}$' and queuing delay '$Delay_Q$' respectively. Latency in our work is measured in terms of milliseconds (ms). Table 2 given below lists the latency and bandwidth rate involved in robust multimedia communication using the three methods, DQRMDO method, hybrid HEVC encoder [1] and WSE-DCNN [2] respectively. Also to ensure fair comparison between the three methods, similar sample videos of same sizes are employed and provided for reference in table 1.

Table 1 Sample videos for simulation

Folder name	Video name	Number of frames	Video length (sec)	Resolution	
				Width	Height
Animals	elefant_1280p.mp4	1064 (0.35sec) – 3040 fps	0.35	1280	720
	giraffes_1280p.mp4	1194	0.39	1280	720
Food	seafood_1280p.mp4	390	0.13	1280	720
Butterflies	butterflies_960p.mp4	1573	0.52	960	540
	butterflies_1280.mp4	1573	0.52	1280	720

With the above sample videos and sizes into consideration three performance metrics are validated and analyzed.

Table.2. Tabulation for bandwidth and latency using DQRMDO method, hybrid HEVC encoder [1] and WSE-DCNN [2]

Testing video (MB)	DQRMDO		hybrid HEVC encoder		WSE-DCNN	
	Bandwidth	Latency	Bandwidth	Latency	Bandwidth	Latency
Elephant video	880	0.35	748	0.55	528	0.63
Giraffes video	1500	0.70	1020	0.85	900	0.90
Seafood video	255	0.20	204	0.35	187	0.48

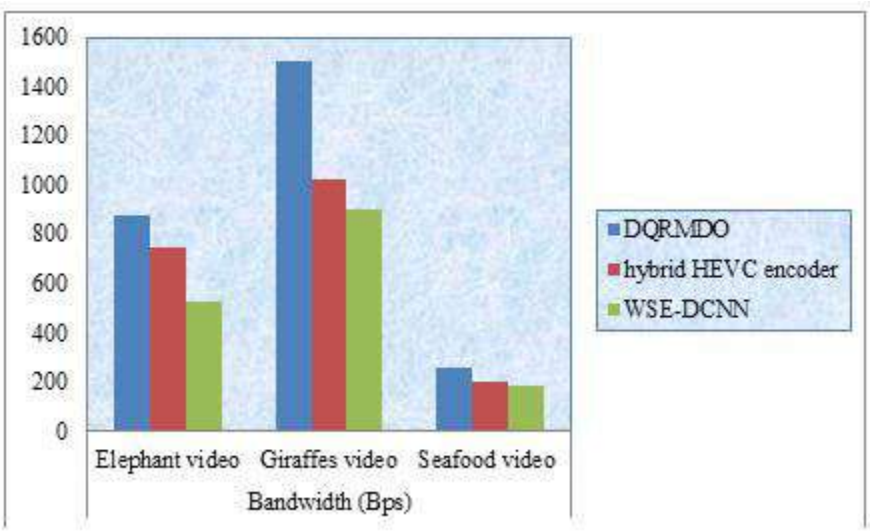

Figure 4 Graphical representation of bandwidth

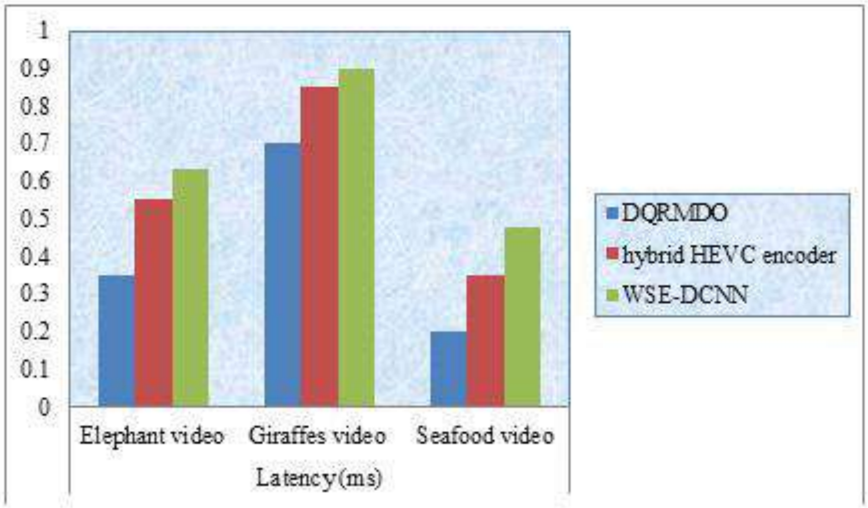

Figure 5 Graphical representation of latency

Figure 4 and figure 5 given above show the bandwidth rate and latency of three different methods, DQRMDO method, hybrid HEVC encoder [1] and WSE-DCNN [2] using three different videos like, elephant, giraffe and seafood of sizes 44, 60 and 17, respectively. With the difference in the size of video the bandwidth rate and latency of each method differs. From the simulation it is found that with a size of 44 the bandwidth using the three methods was found to be 880 bps, 748 bps and 528 bps. In a similar manner, the latency using the three methods was observed to be 0.35ms, 0.55ms and 0.63 ms respective for elephant video possessing size of 44. From these results it is inferred that both the bandwidth and latency consumed in ensuring robust multimedia communication using the proposed DQRMDO method was found to be comparatively lesser than the existing methods [1] and [2]. This was because by applying the Quantile Regression function in determining the fitness of all CU partitioning pattern on the basis of multiple objective functions. Here, multiple objective functions considered in the work were both minimum Rate Distortion cost (RD cost) and Energy Consumption (EC). From these two objective functions, the best fittest CU partitioning pattern among the population was obtained. Finally, among them global optimal solution was determined for identifying the optimal CU partitioning pattern of each CTU in HEVC. This in turn reduced the data transmitted per second and overall the bandwidth rate was said to be improved using DQRMDO method by 18% upon comparison to [1] and 42% upon comparison to [2] with respect to elephant video. In a similar manner, the latency involved was reduced by 36% upon comparison to [1] and 13% upon comparison to [2] with respect to elephant video.

6.2 Performance analysis of throughput

Finally, threshold is measured that represents the percentage ratio between the sample video sent (i.e., frame size) to the sample video received (i.e., frame size). The threshold is measured as given below.

$$Th = \frac{SV_{recvd}}{SV_{sent}} \qquad (17)$$

From the equation (17) the throughput rate 'Th' is measured by taking into considerations the sample videos sent 'SV_{sent}' and sample videos received 'SV_{recvd}'. It is evaluated in terms of percentage (%).

Table 3 Tabulation of throughput using DQRMDO, hybrid HEVC encoder [1] and WSE-DCNN [2]

S. No	Methods	Throughput
1	DQRMDO	87.17
2	hybrid HEVC encoder	79.48
3	WSE-DCNN	74.35

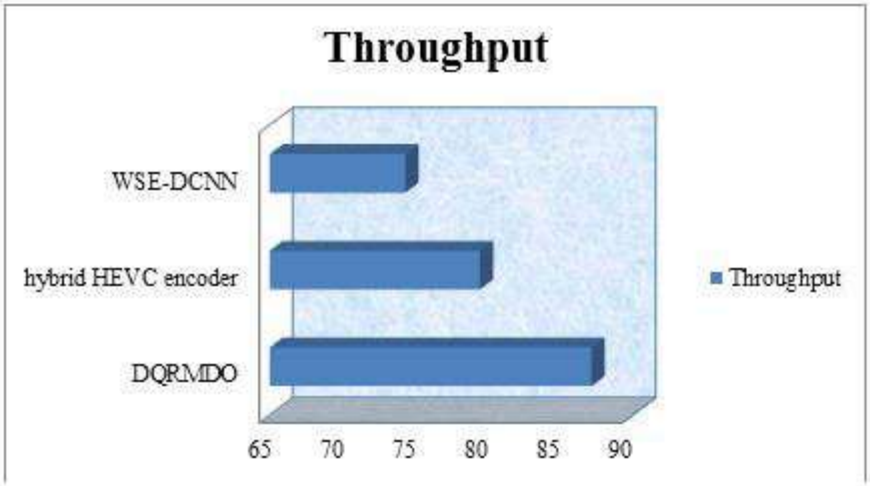

Figure 6 graphical representation of throughput

Figure 6 given above shows the graphical representation of throughput using three methods. To ensure robust multimedia communication in HEVC throughput plays a major role. From the above figure the throughput rate of the proposed DQRMDO method was found to be significantly better upon comparison to [1] and [2]. This is evident from the sample video with frame size of 39 where 34 frames were received usingproposed DQRMDO method, 31 frames using [1] and 29 frames were using [2]. From this result the throughput using proposed DQRMDO method is found to be comparatively better than [1] and [2]. The reason behind the improvement was owing to the application of dynamic dragonfly optimization model. By applying this dynamic model, three distinct processes, namely, separation, alignment and cohesion was applied on the basis of the current frame positioning of an available CU at a definite time instance and the nearest frame positioning respectively. With these two positioning global optimal solution was arrived at among the overall population. This in turn improved the sample video frame size being received and therefore improving the throughput using proposed DQRMDO method by 10% upon comparison to [1] and 7% upon comparison to [2] respectively, therefore corroborating the objective of robust multimedia communication.

7. CONCLUSION

In this paper, a novel method called Dynamic Quantile Regressive Multiobjective Dragonfly Optimization (DQRMDO) employing HEVC video encoder/decoder on 8 core DSP processors using short video dataset have been proposed, which employs Quantile Regression function and Dynamic Dragonfly Optimization are subjected to multi objective function to HEVC using multicore DSP for robust multimedia communication. In this regard, two distinct processes were performed wherein the sample short videos were first subjected to multi objective function to reduce rate distortion cost and improve energy efficiency using Dynamic Quantile Regressive Multiobjective Dragonfly Optimizer. Second, by optimizing coding unit partitioning pattern of CTU in HEVC video encoder/decoderidentified significantly the frames in the video imagesto achieve robust multimedia communication. Experiments were conducted on short videos dataset to test the performance of the proposed method. Experimental results show that the proposed DQRMDOmethod achieved high bandwidth and throughput with minimum latency upon comparison to the state-of-the-art methods.

REFERENCES

[1]. Vicente Galiano, HéctorMigallón, Miguel Martinez-Rach, Otoniel Lopez-Granado, Manuel P. Malumbres, "On the use of deep learning and parallelism techniquesto significantly reduce the HEVC intra-coding time", The Journal of Supercomputing, Springer, Sep 2022 [hybrid HEVC encoder]

[2]. SoulefBouaafia, RandaKhemiri, SeifeddineMessaoud, Olfa Ben Ahmed, FatmaEzahraSayadi, “Deep learning-based video quality enhancement for the new versatile video coding”, Neural Computing and Applications, Springer, Feb 2022 [Wide-activated Squeeze and Excitation Deep Convolutional Neural Network (WSE-DCNN)]

[3]. Mohammed Bey Ahmed, Bretagne-Sud, JalilBoukhobza, ENSTA Bretagne,M’hamedBougara, LMSS, AlgeriaDaniel Menard, “Energy-Aware HEVC Software Decoding OnMobile Heterogeneous Multi-Cores Architectures”, ACM, Sep 2022

[4]. Mai Xu, Tianyi Li, Zulin Wang, Xin Deng, Ren Yang and Zhenyu Guan, “Reducing Complexity of HEVC: A Deep LearningApproach”, IEEE Transactions on Image Processing, Dec 2018

[5]. Jingyao Xu, Mai Xu, Yanan Wei, Zulin Wang and Zhenyu Guan, “Fast H.264 to HEVC Transcoding: A DeepLearning Method”, IEEE Transactions on Multimedia, Oct 2018

[6]. Peisong He, Haoliang Li, Hongxia Wang, Shiqi Wang, Xinghao Jiang, IEEE, Ruimei Zhang, “Frame-wise Detection of Double HEVCCompression by Learning Deep Spatio-temporalRepresentations in Compression Domain”, IEEE Transactions on Multimedia, Oct 2020

[7]. Adam Wieckowski , Jens Brandenburg, Benjamin Bross , Member, IEEE, and DetlevMarpe, “VVC Search Space Analysis Including anOpen, Optimized Implementation”, IEEE Transactions on Consumer Electronics, Vol. 68, No. 2, May 2022

[8]. Sonda Ben Jdidia, FatmaBelghith, Nouri Masmoudi, “A high-performance two-dimensional transform architectureof variable block sizes for the VVC standard”, Journal of Real-Time Image Processing, Springer, Sep 2022

[9]. Sunil Kumar B S, A.S. Manjunath, S. Christopher, “High efficient video coding using weighted entropy with optimizedquantization matrix”, Journal of King Saud University –Computer and Information Sciences, Elsevier, Dec 2017

[10]. D. Rodríguez Galiano, A .A . Del Barrio, G. Botella a , D. Cuesta, “Efficient emb e dding and retrieval of information for high-resolution videos coded with HEVC”, Computers and Electrical Engineering, Elsevier, Dec 2019

[11]. ChamindaT. E. R. Hewage, ArslanAhmad, ThanujaMallikarachchi, NabajeetBarman, Maria G. Martini, “Measuring, Modeling and IntegratingTime-Varying Video Quality in End-to-EndMultimedia Service Delivery: A Reviewand Open Challenges”, IEEE Access, Jun 2022

[12]. Sovann Chen, SupavadeeAramvith, Yoshikazu Miyanaga, “Learning-Based Rate Control for High Efficiency Video Coding”, Sensors, Mar 2023

[13]. S.Jothi, A. Chandrasekar, “An Efficient Modified Dragonfly Optimization BasedMIMO-OFDM for Enhancing QoS in Wireless MultimediaCommunication”, Wireless Personal Communications, Springer, Aug 2021

[14]. Hongwei Lin, Xiaohai He, Linbo Qing, QizhiTeng, Songfan Yang, “Improved Low-Bitrate HEVC Video Coding using Deep Learning based Super-Resolution and Adaptive Block Patching”, IEEE Transactions on Multimedia, Jul 2019

[15]. Xinpeng Huang, Ping An, Qiuwen Zhang, “Efficient AMP decision and search rangeadjustment algorithm for HEVC”, EURASIP Journal on Image and Video Processing, Springer, Oct 2017

[16]. Zhi Ma, Songlin Sun, “Research on HEVC screen content coding and video transmission technology based on machine learning”, Ad Hoc Networks, Elsevier, Jul 2020

[17]. EhabGhabashnehPurdueUniversityChandanBothraPurdueUniversityRameshGovindanUniversity of Southern CaliforniaAntonioOrtegaUniversity of Southern CaliforniaSanjay Rao, “Dragonfly: Higher Perceptual Quality For Continuous 360° VideoPlayback”, ACM, Sep 2023

[18]. Osama S. Faragallah, Ashraf Afifi, Hala S. El-Sayed, Mohammed A. Alzain, JehadF. Al-Amri, FathiE. Abd El-Samie, WalidEl-Shafai, “Efficient HEVC Integrity Verification Scheme forMultimedia Cybersecurity Applications”, IEEE Access, Sep 2020

[19]. ZhaoqingPan, XiaokaiYi, Yun Zhang, Hui Yyan, Fu Lee Wang, Sam Kwong, “Frame-level Bit Allocation Optimization Based onVideo Content Characteristics for HEVC”, ACM Trans. Multimedia Comput. Commun. Appl., Vol. 16, No. 1, Article 15. Publication date: March 2020

[20]. Ray Garciai, Damian Ruiz-Collii, Hari Kalvai, Gerardo Fernández-Escribano, “HEVC DECISION OPTIMIZATION FOR LOW BANDWIDTH IN VIDEO CONFERENCINGAPPLICATIONS IN MOBILE ENVIRONMENTS”, Institute of Electrical and Electronic Engineers, Oct 2013