ISSN: 2229-6956 (ONLINE)
DOI: 10.21917/ijsc.2022.0390

META-HEURISTIC OPTIMISATION FOR OPTIMAL VIDEO QUALITY ENHANCEMENT

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Abstract

We have seen a rapid development in technology over the past few years, from basic mobile phones to highly advanced surveillance monitoring systems that can record and analyze video clips. The process of video capture inevitably leads to a decline in overall video recording quality. Inadequate lighting is due to either an open aperture or a slow shutter speed. Images taken in such conditions typically have poor contrast and noisy backgrounds. If the contrast in your video is off, it could be because of a malfunctioning imaging device or an untrained operator. These two outcomes are equally plausible. When recording videos, this causes a loss of the dynamic range that could have been captured. Because of this, the video may appear distorted or washed out, and some of the finer details may be lost. In order to lessen the impact of these problems on the viewer experience, contrast enhancement techniques can be used to boost the visual quality. Work presented here will take a two-pronged approach to addressing the aforementioned problems. Videos can be compressed and their contrast can be increased, both of which are useful techniques that complement one another. Video quality can be improved with the help of a method called ant colony optimisation ACO based image quality enhancement. The frames of a video can be analyzed in greater detail using this hybrid method than with the conventional method. The noise is further reduced when the non-divisible median filter is used. To do this, the study develops an optimisation to attain increased rate of peak signal to noise rate than the other existing methods. After examining available options, the researchers settled on the DLACDHE procedure as the best option. Based on the results, it is reasonable to infer that the proposed strategy offers better contrast enhancement than the conventional methods.

Keywords:

Classification, Ant Colony Optimisation, Improved Video Quality Enhancement

1. INTRODUCTION

Big data processing, cloud computing, and the Internet of things (IoT) are all a part of the growing multimedia portfolio [1], and they all have an impact on people daily lives. Multimedia IoT (M-IoT) is widely regarded as a foundational networking technology [2] for connecting and interacting with people, hospitals, factories, and commonplace things like cameras, cars, and sensors. This is due to the fact that M-IoT can establish connections and exchange data with a wide range of devices. As an added bonus, M-IoT systems also make use of networking, computer vision, and image processing technologies [3]. Despite this, they can be used in in-car assistance systems for things like crime and fire detection, as well as in remote sensing for things like tracking high-speed objects. A number of obstacles, however, must be overcome in order to process multimedia data efficiently [4]. Considerations such as data size, security, reliability, storage, and processing power fall under this heading.

M-IoT stands out from IoT because it has more sophisticated features, such as dependable data delivery, than IoT. As a result, strict quality-of-service (QoS) requirements and the need for a more streamlined network architecture are essential. The term QoE refers to the perspective of the customer regarding QoS. QoE, or quality of experience, can be measured in two ways: objectively and subjectively. Quality of experience (QoE) is a term that is subjective to each user and can vary widely depending on the type. Although the objective quality of experience is required for computing a network MOS, service providers are more concerned with the subjective quality of experience [5]. Sending, storing, and sharing multimedia files (such as audio, video, and image files) presents a unique set of difficulties [6]. Furthermore, feature extraction, event processing, encoding/decoding, energy-efficient computing, quality of service, and quality of experience are all required for processing M-IoT data [7].

The proliferation of new media platforms and services has led to an explosion in the availability of video games, streaming services, and other media consumption options. Higher image resolution, specifically 4K and 8K, is necessary due to the QoS requirements of end users, especially for gaming and monitoring tasks. In the traditional approach to multimedia encoding, data is compressed only once, and then decoded each time the media is played. The uplink ability to transmit data is crucial for M-IoT gadgets. Devices in the M-IoT with limited processing power face difficulties in this latter case. This has led to widespread adoption of versatile video coding (VVC), a robust approach to multimedia encoding and decoding. This new generation of video coding, known as VVC [8], was created in July of 2020 by a group of experts in the field of video communication (JVET). We did this as a follow-up to HEVC [9]. VVC is the next generation of video coding technology, and it could reduce BD bit rates by as much as 30 percent without sacrificing video quality. Compression artifacts like these can lead to a subpar quality of experience (QoE), despite VVC best efforts to preserve high-quality compressed video with additional encoding features. Therefore, there is an urgent need to enhance the QoE of VVC-compressed video.

However, since VVC still employs a block coding and quantization structure, a number of artifacts, such as blocking artifacts, blurring artifacts, and ringing artifacts, remain. There is a noticeable drop in visual quality as a result of the blocking artifacts. Though these imperfections can't be fixed, they can be mitigated by using filters that focus on correcting them. In order to lessen the number of visible artifacts and boost the overall quality of videos and still images, loop filters, for example, are indispensable.

Unlike HEVC, which uses out-of-band filtering methods, the VVC standard makes use of in-loop filtering methods like the de-blocking filter (DBF), sample adaptive offset (SAO), and adaptive loop filter (ALF). These filters enhance the reconstructed video aesthetic by getting rid of the compression-induced artifacts.

Actually, the DBF framework is designed with smoothing filters based on discontinuities to lessen artifacts at block boundaries [10] [11]. The SAO step is applied as a filter to reduce ringing artifacts by compensating for them after the DBF step, which shifts samples using the encoder lookup table and analyzes signal amplitudes using a histogram [12]. Adaptive loop filtering (ALF) is the most up-to-date and innovative loop-filtering approach in visual fidelity coding (VVC). As shown in [13], ALF helps to minimize discrepancies between a reconstructed image and its original form. This kind of conventional in-loop filtering can be useful for eradicating some artifacts, but it not easy to get rid of the complex distortion introduced by video compression. Our solution to this problem is the use of strong deep learning strategies. When it comes to visual content identification and analysis, convolutional neural networks (CNNs) are the most powerful and effective processing methods [14] [15].

The proposed methods use Ant Colony Optimisation (ACO) based post-processing to minimize artifacts. The proposed method adds new, robust in-loop optimisation to the standard without using those more conventional approaches. In reality, the primary objective is to enhance the quality of the compressed video by removing artifacts brought about by the compression itself. The quality of the user experience as a whole is enhanced by the proposed method.

2. LITERATURE SURVEY

Deep learning is a branch of AI that has recently shown impressive results in computer vision tasks [4] [5], especially in video encoding [6] [7], and has even been used by government agencies. In the area of video encoding, in particular, deep learning has shown impressive results. The capabilities of HEVC and VVC in intra- and inter-prediction, transformation, quantization, and loop filtering have all been enhanced through the use of deep neural networks. Enhancements to loop filtering using deep neural networks have also been implemented.

The HEVC inter-prediction process using machine learning can be found [8]. The amount of RD complexity produced by the proposed algorithm is sufficient enough to yield desirable results. For better intra-coding performance in HEVC, [9] also introduces a fast algorithm based on CNN.

By exchanging DBF and SAO for an improved convolutional neural network, Pan et al. [16] proposed an in-loop filtering for HEVC that would eliminate artifacts (ED-CNN).

To replace these filters, this procedure would be carried out. The proposed strategy reduced BD occurrence by 6.45% while raising PSNR by 0.238 decibels. As a new approach to DBF and SAO in intra-coding HEVC, the variable-filter-size residue learning convolutional neural network (VRCNN) was proposed in. This strategy is referenced in [17]. Simulation results show that using the proposed approach can reduce BD costs by 4.6%.

To enhance the loop-through filtering and post-processing of the VVC standard, Ma et al. [18] developed a novel CNN model called the MFRNet. The proposed method was applied to a VVC test model to enhance video quality. Dense residual convolutional neural networks (DRNs) were also proposed for use in VVC. All of the operations in this network, which would be used after DBF and before SAO and ALF, are based on in-loop filtering. The improved DAG-SVM classifier model is necessary for H.266/fast VVC intra-CU coding technique to be implemented. The complexity of CU partitioning is simplified with this method. The proposed model has been experimentally shown to have a potential encoding efficiency of 54.74%.

To avoid unnecessary VVC block partitioning, [19] proposed a lightweight neural network (LNN) based on a fast decision algorithm. The proposed model achieves a happy medium between the competing requirements of keeping the encoding simple and keeping the compression efficiency high. However, when applied to an M-IoT context, the VVC standard emphasis on experience quality is overlooked by these techniques.

With the goal of enhancing the quality of VVC videos and achieving coding gains, we propose an in-loop filtering strategy based on wide-activated squeeze-and-excitation deep CNN (WSE-DCNN).

3. PROPOSED METHOD

Not to limit our imaginations too much, but our proposed M-IoT scenario for a smart city is shown in Fig.1.

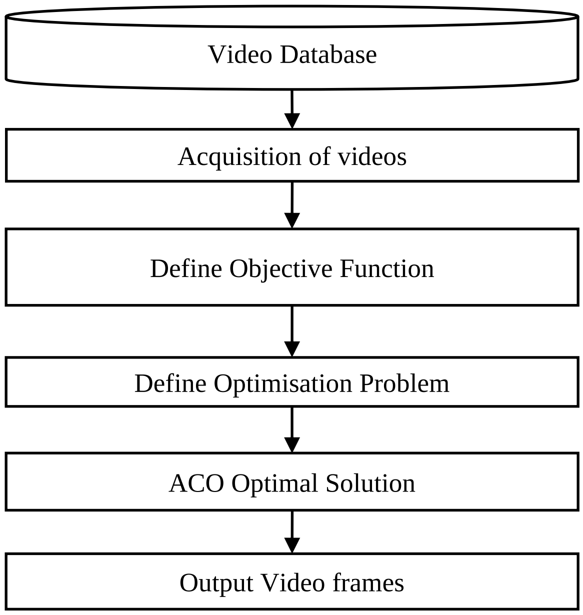

Fig.1. Architecture of Video Quality Enhancement

It is made up of various M-IoT devices, such as cameras and players, that can gather M-IoT content from their surroundings. The gathered multimedia data is then sent to the central cloud computing system through the network layer, making use of a variety of transmission technologies such as LP-WAN. Users whose devices have limited processing power may find it difficult to transmit uplink data, a primary concern for M-IoT devices. Delay, jitter, and packet loss rate are just some of the metrics that can be considered at this stage. We are seeing a rise in the importance of centralized computing for tasks such as the encoding and decoding of M-IoT data.

Data acquired via M-IoT is only compressed once before being decoded on-demand for playback. The encoding and compression of video data has historically made use of both spatial and temporal redundancies. When the vast amounts of collected multimedia data are structured or unstructured, moving at a high velocity, and having different resolutions, video quality is seen as a potential challenge in the VVC standard. Therefore, it is necessary to enhance the video quality at this time. Thus, experience quality is the metric that should be optimized for, as its efficacy is directly related to the performance of the video quality. The formulation in [36] uses the modeling presented there to explain the relationship between bit rate and quality of experience is an equation that can be used to calculate the quality of effort per unit of effort.

$$QoE_{BR} = a\times\log(BR)+b \tag{1}$$

where a and b are experimentally determined coefficients. However, unlike the PSNR metric, this parameter will be used in the proposed WSE-DCNN-based in-loop filtering to establish video quality.

3.1 OBJECTIVE FUNCTION

The goal is to make the most efficient use of available bandwidth while still satisfying the delay and QoE requirements of all of the concurrent video streams. To reach the objective, the queue buffer size should be minimized, and the queuing delay should be optimized across all media streams. As a result, a QoE-optimized, latency-optimized, lower-bit-rate version of the video streaming service is achieved by employing packet drops, which maximizes the deadline of decoding constraints while running under full VQ.

$$\min_{\rho,E[X]} E\left[\sum_{r=0}^{R^k-1}\sum_{t=0}^{T^k-1}\bar{W}_{r,t}^{k}\right] \tag{2}$$

$$s.t \quad \bar{W}_{r,t}^{k} \le \bar{W}_{r,t,\max}^{k} \quad \forall k = K, \forall t = T, \forall r = T$$

$$D_{\max}^{k} \ge D_{overall}^{k}$$

$$\sum_{r=0}^{R^k-1}\sum_{t=0}^{T^k-1} E\left[X_{r,t}^{k}\right] \le C^k \quad \forall k \in K \tag{3}$$

By defining the objective function in this way, we can reduce the amount of time spent waiting for the video stream. It takes less time to wait for a VQ than it does to decode q_r^t it as the average wait time $\bar{W}_{r,t,\max}^{k}$ is less than a month $D_{\max}^{k} \ge D_{overall}^{k}$. For at least k video streams, this indicates a decrease in service quality $D_{\max}^{k}$ that does not last past the decoding deadline $\bar{W}_{r,t,\max}^{k} \approx f^{-k}$.

The mobile service provider sets the standard for what constitutes a satisfactory quality of experience (QoE) stream. The end user throughput, denoted by C^k, sets the upper bound on the total service rates of video stream k with VQ.

$$\sum_{r=0}^{R^k-1}\sum_{t=0}^{T^k-1} E\left[X_{r,t}^{k}\right] \le C^k \tag{4}$$

3.2 OPTIMISATION PROBLEM

By allocating resources across layers, we are able to reduce the amount of power sent from the base stream to the k users, thereby saving energy. Now, the study has figured out how to fairly divide up our resources, and satisfying the delay constraints of each individual video stream.

$$\min_{P,x} E\left[\frac{1}{L}\sum_{k=1}^{K}\sum_{l=1}^{L} x_l^k P_l^k\right]$$

$$s.t.E\left[\frac{1}{L}\sum_{k=1}^{K}\sum_{l=1}^{L} x_l^k P_l^k\right] \le P_{\max}$$

$$\sum_{k=1}^{K} x_l^k \le 1$$

$$x_l^k \in \{0,1\}, P_l^k \ge 0$$

$$\bar{W}^k \approx \bar{W}_{\max}^{k} \tag{5}$$

The goal of the demonstrated optimization problem is to lessen the downlink OFDMA transmission power. Maximum allowable power at the base streams is indicated by the parameter P_{max}. The $\sum_{k=1}^{K} x_l^k \le 1$ and symbol $x_l^k \in \{0,1\}, P_l^k \ge 0$ represents both the binary variable denoting the allocation of resource blocks and the single recipient of those allocations. In the context of the video delay constraints $\bar{W}^k \approx \bar{W}_{\max}^{k}$, this is the maximum delay $\bar{W}_{\max}^{k}$ that can be tolerated by stream k.

$$\bar{W}_{\max}^{k} = E\left[\sum_{r=0}^{R^k-1}\sum_{t=0}^{T^k-1}\bar{W}_{r,t}^{*k}\right] \forall k \tag{6}$$

The most efficient method of sharing the video stream resources is to group them.

3.3 ACO OPTIMISATION

The presented mathematical model has been implemented in the GAMS environment to efficiently solve the intermediate- and large-scale test problems. The problem being studied, however, is NP-hard, making it not only impractical but sometimes impossible to solve using CPLEX by GAMS. Because of this, an ACO-based algorithm was developed and is also shown here as an example. The ACO employs ten widely used line-balancing rules to provide heuristic direction during the task selection process. This suggests that each ant possesses the freedom to act in any of several predetermined ways.

An example of an algorithm that is inspired by nature is the ACO, which takes its cues from the way ants search for food in their natural habitat. To reduce both the number of mated streams (*NM*) and the total number of streams (*NS*), as stated in the formulation of the mathematical model, is the primary goal of the ACO algorithm proposed in this paper. The smoothness index (*SI*), which is another measure of performance, has also been built into the algorithm. As an example of the formula to minimize the objective function: The objective function can be written as:

$$\text{minimize Obj} = w_1\cdot NM + w_2\cdot NS,$$

where w_1 and w_2 - weighting parameters whose values establish the relative importance of *NM* and *NS*.

The *SI* is used to determine which of several possible solutions is best when several of them have the same value for the objective function.

$$SI = \frac{100\sqrt{\sum_{m\in M} d_m \sum_{j\in J}\sum_{k\in\{1,2,3\}}\left(MaxWT_m - WT_{m(j,k)}\right)^2}}{CT \times NS} \tag{7}$$

where

m - model; j - packet; k - data stream,

$WT_{m(j,k)}$ - workload time and

$MaxWT_m$ - maximum workload time.

In Fig.3 we can see the proposed ACO algorithm high-level design. The Fig.3 shows that after the algorithm parameters have been set, a new colony is released into the wild. A small fraction of the colony population is released at a time in order to construct robust solutions. Most studies follow a single rule to provide heuristic information, but this is far from ideal. However, in order to speed up the process of finding a solution, the current study allows each ant to choose a rule at random. Each of the ten heuristics has a one in ten chance of being chosen at random, rather than using any knowledge of the pheromones associated with the task at hand.

The pheromone at the solution edges will be updated if the value of the objective function (*Obj*) for the newly obtained solution is less than the value for the best solution found so far ($Obj>Obj^*$).

The cardinality, or number of items in a set, is represented by the symbol card (X), and the set of actions, or AT_{jk}, is the set of options open to each player in that position (j,k).

$$d_m = \frac{D_m}{\sum_{m\in M} D_m} \tag{8}$$

where,

d_m - proportional model demand, and

$card(X)$ - number of elements of set X.

Pheromones are placed between tasks and the workstreams to which they are assigned using the formula.

$$\tau_{i(j,k)} \leftarrow (1-\rho)\tau_{i(j,k)} + \Delta\tau_{i(j,k)}$$
$$\Delta\tau_{i(j,k)} = Q/Obj; \tag{9}$$

where

ρ - evaporation rate and

Q - user-determined parameter, respectively.

If it turns out that the newly found answer is better than the current one, then the new answer will replace the current one as the optimal one, and the amount of pheromone released will be doubled.

$$\text{if } Obj<Obj^*\text{: } Obj^* \leftarrow Obj \text{ and } SI^* \leftarrow SI;$$
$$\text{if } Obj=Obj^* \text{ but } SI<SI^*\text{: } SI^* \leftarrow SI \tag{10}$$

When a new ant is released into the wild, it immediately sets to work coming up with a novel strategy for preserving equilibrium. The process is repeated until the entire ant colony has found a workable solution, and if a better answer is found, the current best answer is swapped out. When an entire colony has completed its journey, a new colony is started, and all of the ants within it work together to find solutions to problems by employing the most modern strategies available. Each colony will go through this process until they have had their chance, at which point the algorithm will end after reporting the best solution.

The parameters, the termination criterion, and the representation of the solution all play a role in the performance of a heuristic or meta-heuristic algorithm. On the other hand, the decomposition technique is crucial. After opening the first mated stream, a random side is selected using the solution-building procedure of the ACO proposed here (left, right, or under). This allows us to guarantee that the algorithm proposed solutions are always workable. By utilizing the heuristic information obtained from 10 different heuristics typically used in the line balancing domain. The following determines the selection probability of task i for the position (j,k). The probability of being selected for a given role is greatest for the option with the highest $p_{i(j,k)}$.

$$p_{i(j,k)} = \frac{\left[\tau_{i(j,k)}\right]^{\alpha}\left[\eta_i\right]^{\beta}}{\sum_{h\in Z_i}\left[\tau_{i(j,k)}\right]^{\alpha}\left[\eta_h\right]^{\beta}} \tag{11}$$

where

α - pheromone weight;

β - heuristic information weight to find the task selection process,

Z_i - candidate task list when a task is selected i.

$\tau_{i(j,k)}$ - pheromone between position (j,k) and task i and

η_i - heuristic information.

To implement the balancing solution, the earliest start times of the subsequent tasks assigned to each workstream are set to the time at which the task i for each model is completed t_{im}^{f}. In this way, you can rest assured that you won't have to start a new task until the one you were supposed to be working on before it is ready to be started. Additionally, the stream time is synced with the active workstream time, and a new side is chosen at random (left, right, or under). As long as there is another side with available capacity, a new side (i) will be selected at random if the current side (j) is unable to complete a task. This holds true regardless of whether or not both sides have available capacity. In the event that the new side stream time ($st_m(j)$) is greater than the existing side stream time ($st_m(i)$), the new side will take precedence. Once the resources at the currently active mated-capacity stream have been depleted and there is no open task, a new mated stream will be opened and the task-assignment procedure will be repeated until there are no more open tasks.

4. EXPERIMENTAL RESULTS

In order to achieve what we set out to do, we made use of the publicly accessible and sizable video dataset known as BVI-DVC. For the sole intent of training deep video compression algorithms, this dataset was crafted. All of the chosen sequences are progressive scanned with a spatial resolution of 3840 by 2160, at frame rates between 24 and 120 frames per second, with a bit depth of 10 bits, and in a YCbCr 4:2:0 format, as per the cited research in [41]. Without cropping any scenes, we reduce each of them to 64 frames using the segmentation method. 200 videos were spatially down-sampled to 19201080, 960540, and 480270 using a Lanczos third-order filter. The data was enriched and the variety of information collected was expanded as a result. Totaling 800 video sequences, the BVI-DVC dataset was shot in four different resolutions and covers a wide variety of topics.

4.1 DISCUSSION

The results of AMBE-based experiments for the first 10 frames using the proposed approach and the two other common methods are presented in Table.1. These findings are based on the results of the experiments. The average AMBE obtained from the three methods are shown in Table.1.

Table.1. Absolute Mean Brightness Error (AMBE)

Frames	ALF	SAO	ACO
100	17.861	17.385	12.656
200	17.810	17.344	12.170
300	18.752	17.233	12.272
400	17.628	17.121	6.642
500	18.883	17.202	12.201
600	19.693	17.354	5.366
700	19.663	17.283	12.241
800	17.628	17.213	11.948
900	18.883	17.101	12.029
1000	18.610	17.223	7.817

Comparing the proposed method to the two reference methods, it shows a 45% and 41% improvement in absolute mean brightness error, respectively. This proves that the suggested approach is the best one. The video quality should still be quite high as measured by the PSNR even when the DACDHE method is used to reduce the AMBE value to its absolute minimum. The PSNR measurement outcomes are shown in Table.2.

Table.2. Peak Signal to Noise Ratio (PSNR)

Frames	ALF	SAO	ACO
100	25.049	29.707	35.893
200	24.918	21.384	35.913
300	25.059	31.094	35.843
400	24.938	32.744	36.592
500	24.928	32.400	35.843
600	24.918	34.536	36.622
700	24.918	34.567	35.843
800	26.517	25.950	35.812
900	25.049	28.775	35.843
1000	26.943	27.773	36.642

The Table.2 shows that the ACO technique, which makes use of a higher PSNR value, achieves better results in improving the quality of video frames. Because of this, the ACO technique was able to generate high PSNR and great video quality. A measure of entropy is used to ensure that this updated video retains the same level of detail as the source material. In order to compute entropy, refer to Table.3.

Table.3. Entropy

Frames	ALF	SAO	ACO
100	7.928	7.138	9.669
200	7.887	8.151	9.629
300	7.158	8.130	9.669
400	7.199	8.120	9.588
500	7.229	8.141	9.609
600	6.946	8.130	9.609
700	6.996	7.918	9.669
800	7.007	7.088	9.659
900	6.986	7.118	9.700
1000	6.774	7.108	9.619

This means the new ACO is great at preventing videos from losing their aesthetic quality. The percentage increases of 31% and 21% are based on comparisons to the efficiency of the SAO and ALF approaches, respectively. With the ACO in place, we were able to greatly enhance the video quality.

5. CONCLUSION

The primary goal of this paper is to demonstrate how ACO can be used to enhance video quality. The proposed approach is implemented to aid the centralized cloud in its pursuit of the required user-specified video quality in the context of a smart city where M-IoT is used. There has been a 17%-35% improvement in video quality over the current state of affairs. Combining contrast enhancement and histogram equalization into a single operation produces a higher-quality image than the original. Therefore, the approach proposed has been shown to be useful for improving video quality in general.

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