Secure and Efficient Video Transmission in VANET

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***Abstract*:** Currently, vehicular communications have become a reality used by various applications, especially real time video transmission. However, the video quality received is penalized by the poor characteristics of the transmission channel (availability, non-stationarity, the ration of signal-to-noise, etc.). To improve and ensure minimum video quality at reception end, we propose in this work a mechanism entitled “Secure and Efficient Transmission of Videos in VANET (SETV)”. It's based on the "Quality of Experience (QoE)" and using hierarchical packet management. This later is based on the importance of the images in video streaming. To this end, the use of transmission error correction with uneven error protection has proven to be effective in delivering high quality videos with low network overhead. This is done based on the specific details of video encoding and actual network conditions such as signal to noise ratio, network density, vehicle position and current packet loss rate (PLR) not to mention the prediction of the future DPP.

Machine learning models were developed on our work to estimate perceived audio-visual quality. The protocol previously gathers information about its neighboring vehicles to perform distributed jump reinforcement learning. The simulation results obtained for several types of realistic vehicular scenarios show that our proposed mechanism offers significant improvements in terms of video quality on reception and end-to-end delay compared to conventional schemes. The results prove that the proposed mechanism has showed 11% to 18% improvement in video quality and 9% load gain compared to ShieldHEVC.

***Keywords*:** VANET, Machine learning, Forward error correction (FEC), Unequal error protection (UEP), High-resolution video, HEVC, Quality of Experience (QoE)

1. Introduction

These last years, real-time video applications are developed and improved rapidly. In addition, VANET should provide support for a large range of distributed applications, such as traffic alerts, independent driving capabilities, and the sharing of medical information in video format. All these improvements allow an important number of services and programs to be easily accessed to users. In addition, remote hospital care is expected to generate large amounts of data thanks to its hundreds of built-in sensors, such as multiple cameras, sonar, radar, and light detection and distance (LIDAR) [1]. In this context, the growth of video-enabled vehicles with live coverage supports both opportunities and challenges. For example, it gives an accurate picture of an accident or the health state of a patient hospitalized remotely. The main outcome of this work is the reduction of the reaction.

Consequently, the main objective is to propose a solution which resists the criteria of unreliable wireless connections such as the conditions of the channels, the traffic rates varying over time and the limited access to resources. This solution must protect video transmission with a better "QoE" [2].

After analyzing the problems mentioned above, we put a solution called "SETV" which takes into consideration the criteria of the VANET network and driven by QoE to guarantee high resolution video transmission. It is based on our previous work, published in [3].

SETV uses the "Ant Colony Optimization (ACO)" [4] to solve computational problems in real-time since this probabilistic algorithm is simulated according to the behavior of the ant. In our work, we considered the "Packet Loss Rate", network density, node positions, video codec type, and frame type. ACO provides protection against Unequal Error Protection (UEP) [5] in which only the most important videos are protected with appropriate redundancy without forgetting that the videos are encoded with the H265-HEVCstandard [6]. Also, machine learning has been used to estimate the overall audio-visual quality in a single function.

Our article is structured as follow: section 2 introduces the related works; section 3 presents SETV followed byan evaluation study in section 4. In the end, section 5 presents a conclusion and prospective.

2. Related works

Varied mechanisms are used to ameliorate the multimedia packet quality in linked vehicle broadcasts, more specifically in VANET scenarios. Video transmission reliability can be realized when employing an adaptive multi-use strategy for Media Access Control (MAC) throughput [7]. The optimization framework uses the Road Unit Packet Transmission Rate (RSU) and channel statistics to fine-tune the MAC transmission functionality. Although this optimization improves video broadcasting, the main concern is to minimize the size of the read blocks and reduce start-up time.

Other mechanisms have been proposed in the literature that employs erroneous correction techniques. An example is the "Optimized Cross-Layer FEC (OCLFEC)" [8]. It uses Luby Transform to encode the data according to priority values, which are based on calculating the root mean square error of each frame. A supplemental error correction code, "Rate Compatible Parity Check (RCPC)", is used to add periodic redundancy check bits. Both correction codes have been optimized for video transmissions on the VANET environment. Using crossover techniques, "Group Of Pictures (GOP)" [9] sequences are evaluated and different weights are assigned to each group of images. Other mechanisms to improve video quality during wireless network transmissions have been proposed based on XOR codes and "Random Linear Coding (RLC)" [10]. Series of experiments have been realized and their results shown that adopting either erase code leads to improvements in video quality, especially in high error rate networks. However, the XOR-based encoding performed better than the RLC paradigm. To improve the proposed mechanisms, the optimal packet block size is calculated, which allows it, in a precise way, to add an amount of redundancy. In doing so, it was able to deliver better quality videos while reducing network overhead.

The Hybrid Video Broadcasting Protocol (HIVE) [11] is a different proposal that uses the advantage of a multi-layered scheme to meliorate video quality. The "HIVE" mechanism is in charge of controlling traffic congestion, it uses an optimized node selection strategy, and the last applies an application layer erasure code. This combination ensures a higher packet delivery rate as well as low packet collisions and low latency. The result of the experiments showed an improvement in Peak Signal to Noise Ratio (PSNR), prompting the authors to claim that a higher "QoE" for end-users was achieved. The ShieldHEVC is a self-adapting mechanism for improving video quality in transmissions over VANETs [12]. This mechanism uses both video characteristics and network details in the process of finding the most appropriate amount of redundancy.

The video details evaluated are those that have the most impact on "QoE", such as frame type and motion intensity, as well as codec related. As for network parameters, it uses vehicle position, "PLR", and "Signal-to-Noise Ratio" (SNR), as well as network density. The evaluation of the mechanism was performed using objective "QoE" measurements and measuring the network overload caused by the additional redundancy. The results obtained after experiments demonstrated that "ShieldHEVC" was able to increase the resilience of video transmissions by protecting the video parts most sensitive to "QoE".

The previously discussed works present important aspects to provide a high perception experience to end-users, but they are not enough to guarantee a high quality of service. Another inconvenience of the mechanism proposed in [7] is that it uses only "RSU" and two-hop communications. One of the main advantages of VANETs is that they allow vehicles to communicate directly with each other, thus eliminating the need for an already deployed infrastructure. The imposition of such limitations hinders the applicability of the mechanism. The downside of the "Optimised-Cross-Layer-Forward-Error-Correction" (OCLFEC) strategy is that it requires several optimization phases, which takes time. This increases delay and therefore degrades "QoE". Moreover, the evaluation process only considers the characteristics of "QoS", which are known to not accurately represent the "QoE" as experienced by end-users. Also, the OCLFEC mechanism excludes the state of the network and the intensity of video movement from the decision-making process. These are important characteristics of any type of mechanism aimed at safeguarding the transmission of video sequences. Indeed, the proposed RLC mechanism does not consider network and video characteristics, which are known to be considered relevant in these cases. Features like video content, codec type, and actual network packet loss are of great importance in the optimization process to calculate an accurate amount of redundancy, which in turn offers better video quality and reduced network footprint. And for the HIVE protocol [11], PSNR scores are known to have a low correlation with the human vision system. In addition to this, the proposed mechanism does not take into consideration the details of the video. This information is of enormous importance in determining the resilience of video material and the level of protection it needs in the event of a network disruption. Nevertheless, one of the main drawbacks of ShieldHEVC is that it only considers the current PLR, which can lead to poor characterization of the state of the network as the past PLR is repeated (or remains the same) in the future.

3. SETV: Secure and Efficient Video Transmission in VANET

Because of the challenges, this work unveils and evaluates the intelligent improved QoE driven and network sensitive video transmission mechanism (SETV). There is a paucity of QoE and motion-sensitive mechanisms capable of utilizing a large amount of network details in conjunction with specific video characteristics. For this reason, the proposed mechanism has been designed to ensure the transmission of video with the highest quality, as well as to reduce the footprint of network overload. The SETV mechanism is an improvement in our precedent work [3]. The new architecture features, and key enhancements are discussed below.

3.1 SETV overview

The SETV mechanism is made up of two phases. The first is machine learning and the second is done in real-time. Figure 1 illustrates the 4 steps of our proposal solution.

The first (1) is to build a video database that has several actual video sequences with different resolutions. Video samples also encompass a wide variety of viewing content that represents commonly watched videos. Additionally, sequences have color and luminance constraints, contain cut and still scenes, in conjunction with multiple levels of distortion and varying intensities of motion. After the video database is fully assembled, exploratory data analysis is performed in the second step (2). This analysis supports the characterization of how distinct video footage is afflicted by both the layout of the network and the impairments introduced by it. To do this, several video sequences are evaluated in a set of network configurations under different levels of disturbance. By analyzing the results, we can typify the QoE-related data that is needed to design fuzzy sets and rules. The third step (3) is responsible for delimiting the specifics of the ACO, the construction graph, the list of candidates, and the heuristic values. The construction graph refers to the association of a set of parameters related to the QoE and network (for example, motion intensity nodes, frame type, and size nodes, as well as loss rate nodes packets) with a set of vertices in the graph. Using the results of data analysis, it is possible to create an effective construction graph. Additionally, the candidate list is an ensemble of top-ranked options for each node, limiting the number of available choices to consider at each build stage, improving real-time performance. Heuristic information is a value assigned to all nodes to direct the Ants to a better route, allowing exploring the problem-dependent conditions found in the data analysis. The last step (4) is the consolidation of all the solutions developed, which includes the ACO met heuristic and fuzzy logic components, to work together in real-time. This machine-learning procedure is essential to provide fast and accurate execution. This is only possible because the reduced number of variables and activities must be managed in real-time.

Figure 2 provides a complete view of the real-time process of the proposed mechanism. The first three steps are responsible for the details related to the video. First, the video frames (1) are converted into packets to be transmitted over the network (2). Then, thanks to cross techniques, several parameters related to QoE referring to the video characteristics are gathered (3). All information is analyzed in the video process of the SETV mechanism. This means that the characteristics of an arbitrary set of video footage being transmitted, such as frame resolution, frame type and size, motion vectors, and Coding Tree Unit (CTU) is mapped to the best-correlated characteristics found in the offline process, which gives the impact on QoE in the event of information loss. This needs an appropriate amount of added redundancies. Then, the network conditions are evaluated (Step 4). To do this, a set of parameters are considered together, such as SNR, current PLR, PLR prediction, node position, and network density.

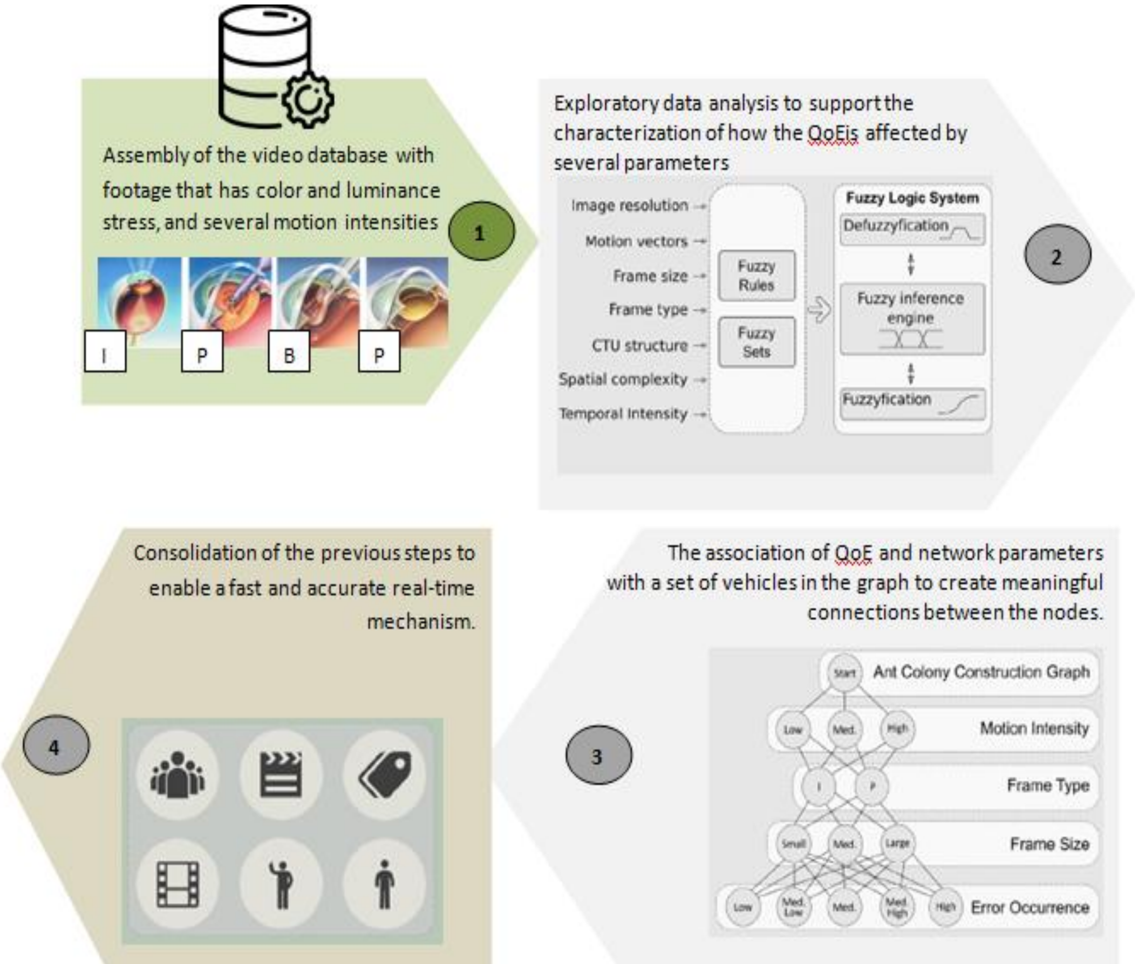

Figure 1. General view of the machine learning process of the SETV mechanism

In principle, none of the parameters mentioned above are in themselves sufficiently precise to define the state of the network or the quality of the communication channels. However, with the combined use of all of them, it is possible to get a very accurate estimation of the network condition. Following this, the decision-making module of the SETV mechanism is fed with all this information, which allows the compute of the amount of redundancies to send with the original video data, called SETV packets (Step 5). Considering that the network-state over time, and therefore diverge from one node (or hop) to another, the network state parameter must be modified at each hop to adapt to this variation (6). Conversely, the video characteristics remain the same throughout the transmission. This condition is exploited by incorporating all the QoE related details into each packet header at the server node level. In doing so, there is no need to perform CPU-intensive tasks, i.e. deep packet inspection, on all packets at intermediate nodes. To store this information, the optional header of IPv6 "Hop-by-Hop" is proposed in [13], making it available whenever needed. For this reason, the effort to adjust the amount of redundancy on each hop is reduced. Ultimately, the SETV mechanism provides end-users with high video quality improving QoE (Step 8).

3.2 SETV design

This section discusses the strategies and components of the SETV. As mentioned earlier, the proposed mechanism has a machine learning procedure which is the basis of real-time capabilities. A further improvement of SETV is the combined use of current and PLR prediction in the real-time process. In doing so, the proposed mechanism better manages the details of the network as the state of the wireless channel changes rapidly over time.

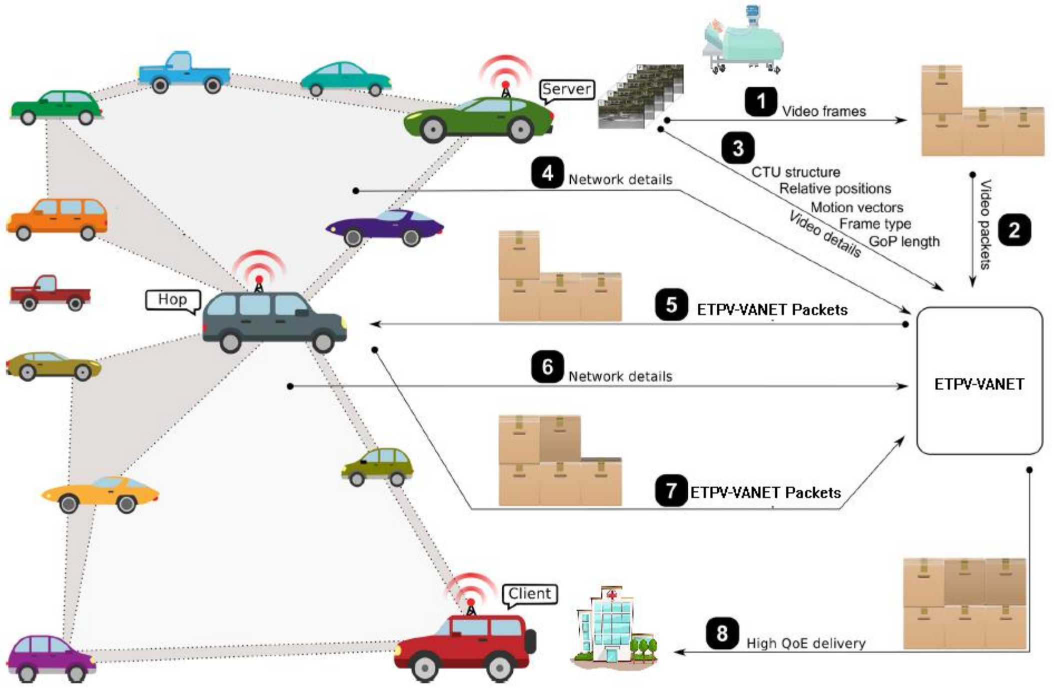

Figure 2.SETV mechanism

Table 1. Notation descriptions

Notation	Meaning
$I_{h(i)}$	"Heuristic Information of the i_{th} node"
$I_{h(ij)}$	"Heuristic Information of the i_{th} and j_{th} nodes"
$d_{(ij)}$	"Length of the arc (i,j)"
q	"One tour (complete walk)"
Q	"Set of tours"
C	"ACO components (nodes)"
L	"Set of partially connected components"

3.2.1 Details of "video characteristics"

Video characteristics are a crucial aspect of defining an explicit amount of redundancies. First, the SETV mechanism identifies three important video characteristics, namely Coding Tree Unit (CTU) [14] details, frame type, and image resolution. The CTU is a new H.265 component to replace the old macro-block structure. It allows a more flexible understanding of the information, which adjust larger block structures yet as more subsection options, being mainly useful to high-resolution videos. Several CTU details are taken into consideration, like the dimensions, type, and the number of subdivisions, to search out how the video was encoded. This is often helpful to compute the number of redundancies needed by a selected scene to boost the QoE for end-users.

Another important parameter is the type of frame. It is well known that some images are more important than others, as presented in [15] in terms of video quality. For this reason, it is important to identify the type of frame that is being transmitted to add an amount of redundancy compatible with it. The last parameter identified is frame resolution. This is necessary to characterize the video size. This information is also used in conjunction with the details of the CTU. Videos with low frame resolution tend to have a small number of large CTU blocks, while videos with higher resolution tend to have larger blocks.

The SETV mechanism evaluates the motion activity of the video. This characteristic is composed of three parameters, namely the spatial complexity, the size of the image and the temporal intensity. Spatial complexity describes the difference in static information from one given frame to another. In other words, how different one static scene is from the next. Using the frame size quantifies this amount. Temporal activity is calculated from the details of the Motion Vector (MV) [16] and represents the range of motion in each video clip. With the combined use of these parameters, it is possible to accurately classify the action rate of a video sequence.

Analysis of all the parameters mentioned above and human expertise provides enough information to construct fuzzy sets, rules, and membership functions. The advantages of fuzzy logic output are in two folds. First, it defines the most appropriate nodes in each candidate list (L_c) that the Ants is heading. Second, since the output is not a precise value but a degree of belonging, this information is considered and only a proportional measure of the distance $d_{(ij)}$ is used to adjust the amount of redundancies. For example, the frame size is classified as {large; way; small}, so the fuzzy logic output would be {0.8; 0.2; 0} for a given image. This means that this weft belongs 80% to the large group and 20% to the medium. As mentioned earlier, the total number of the redundancy and the distance covered by the Ants are equal. And since this frame only belongs to 80% of the large group, it is only considered 80% of the distance $d_{(ij)}$.

Equation 1 gives the total amount of redundancy R_q for a specific tour (full run) q. Let α be the highest degree of membership of node n. The $d_{(ij)}$ is the distance necessary to cover the nodes (n-1) and n.

$$R_q = \sum_{n=0}^{q} \alpha_n \times d_{(ij)n} \quad (1)$$

3.2.2 "Network status" details

The SETV uses five separate parameters to estimate the quality status of the network:

- SNR is a physical medium indicator generally used for spectrum detection and shows the signal level in relation to noise. By itself, this indicator is not a reliable measure of network quality because a strong signal is always lead to an error-free network connection [17]. However, a weak channel signal is most likely lead to a very poor-quality connection. To realize a more holistic indicator, the other metrics are also evaluated.
- The actual PLR present an inverse relation with the SNR, meaning that when one is high the other is low and vice versa. Besides, this indicator provides an assessment of the network closer to the application layer because the SNR is oriented towards the physical spectrum. Thus, they are complementary to each other. However, the actual (or past) PLR is not enough to approve the future behavior of the network. For this reason, the SETV mechanism also predicts PLR. There are several attempts to predict PLR using sparse basic models, time series, and hidden Markov models. However, as the proposed mechanism must run in real-time, this prediction must be easy and quick to calculate. In addition to this, the main goal is not to create a very accurate PLR prediction as this indicator is used along with the other parameters. The PLR forecast was calculated using a weighted arithmetic mean. In our case, a set of the last five PLRs were used as input data, represented by $\{x, x_{n+1}, \ldots, x_5\}$. However, since our weighing input is normalized, the weighted arithmetic means formula is simplified as shown in Eq. 2.

$$avg = \sum_{i=1}^{5} w_i x_i \quad (2)$$

- The adopted set of weights was found through several experiments and defined as {0.4; 0.3; 0.15; 0.1; 0.05}.
- Another parameter analyzed is the network density, which is calculated by dividing the number of vehicles by the whole area of the network. Finding this domain is a challenge because VANETs are highly dynamic networks without a centralized structure. The SETV mechanism solves this problem using the "Bentley-Faust-Preparator" (BFP) convex approximation shell algorithm [18]. This algorithm finds the littlest boundary polygon of all the nodes inside. The BFP algorithm is an approximation because it rejects a non-extreme point in an exceedingly given band whether it belongs to the convex shell boundary. However, the eventual sidelined point is not removed from the limit, making it an honest approximation of the fully convex hull.
- Finally, the last parameter evaluated is the position of the node. The distance between nodes is important due to radio interference and signal attenuation. For this reason, nodes distant from each other tend to require more redundancy to maintain a high-quality video image.

4. Evaluation and results

The objective of SETV is to improve QoE for end-users and to avoid any non-essential network costs. The result is a meticulous use of resources while improving video quality. We first generated an audio-visual quality data set, designed to include resolution, bit rate, bandwidth, packet loss rate, and factors influencing jitter. Table 2 shows the values selected for these influencing factors.

For the evaluation, we use a test rig to come up with benchmark videos with ideal encoders additionally as media and channel settingsto make better models. We have recreated our end-to-end media pipeline using the GStreamer framework for audio and video streaming [19]. A pipeline supported GStreamer has proven to be significantly more robust to network degradation. It allows us to stream video with a packet loss rate of up to 5%. It also gathers relevant Real-time Transport Control Protocol (RTCP) statistics, which is more accurate than inferred network information. Using this test bench, we generated the audio-visual quality data sets for National Institute for Scientific Research (NISR). The precision in statistics ultimately helps us to generate models for estimating perceived quality. The audio-visual quality dataset is designed to hide the most factors influencing network compression and distortion. These factors are quantization, video frame rate, network packet loss rate and filters.

Table 2. Audio-visual quality dataset influence factors

Resolution	**HD1080 (1920x1080 pixels)** **HD720 (1280x720 pixels)**
Bit Rate	"High Quality" (HQ) "Medium Quality" (MQ) "Low-quality" (LQ)
Bandwidth	"High Bandwidth" (2x Max Bit Rate) "Low Bandwidth" (Max Bitrate)
Packet Loss rate (%)	0, 0.1, 0.5
Jitter (ms)	0, 10, 50, 100

4.1 Video sequences and test configuration

The original audio-video sequence is a home care sequence, where we increase the range of encoding configurations and network alterations rather than variations in video content. This unique type of content is potentially quickly annoying observers during the subjective assessment. To avoid this, we divided the whole experience into several sessions and sequences. We have also introduced rejection criteria during post-processing to be able to detect moments and periods of inattention.

Another important parameter that influences the overall perceived quality is the frequent use of I-frames [20]. In the previously mentioned datasets, there is an I-frame every 1-2 seconds due to the high complexity of the movement as well as evenly distributed alterations. In this research, we kept the default value of video I-frame periods, which is10 s, for low motion videos set by the video encoder. This duration of the I-frame video period is then required to use a video sequence that is longer than traditional videos of 10-15 s. The test video has duration of 42 seconds. We produced 32 reference audio-visual files. These reference files have different qualities in terms of the Quantization Parameter (QP), Noise Reduction values (NR) and displayed Frame Rate per Second (FRS). These values are listed in the table 3. The audio coding parameters are retained (mono channel, 16 kHz sample rate, and 24 Kbps bit rate) for all audio-visual sequences. The GStreamer multimedia framework only uses the jitter buffer mechanism to regulate the flow of packets. There is no packet concealment strategy and therefore in our dataset, we suppose that the reported packet loss figures correspond to residual packet loss.

Table 3. Media compression parameters and network impairments

	Video	Audio
Frame Rate	10, 15, 20, 25	Mono, 16kHz, 24 kbps
Quantization Parameter	23, 27, 31, 35	Mono, 16kHz, 24 kbps
Noise Reduction	0, 999	Mono, 16kHz, 24 kbps
Packet Loss Rate (%)	0, 0.1, 0.5, 1, 5	0, 0.1, 0.5, 1, 5

An emulated network is accustomed to transmitting and record the audio-visual sequences. The audio and video streams are captured with our custom software supported GStreamer, which allowed us to collect detailed transport protocol statistics and separately report the precise network packet loss values for video and audio streams. The Item network emulator has been deployed to provide network packet loss conditions. Network Packet Loss is activated until after the primary second of audio and video transmission. This allows us to get more realistic results.

4.2 Analysis and results

With the new data set, we extended our search and first conducted an extensive screening process to find better performing models using the Workshop at the University of Waikato (Weka) [21]. We have chosen the 10-sample cross-validation using the default settings for each algorithm listed. To compare the performance of our model with popular methods, we have developed our SETV model, OCLFEC model [8], HIVE model [11], and RLC model [10]. We train all the methods and measure their accuracy using 10-sample cross-validation. We are also interested in the case of 4-sample cross-validation for deep learning. Also, we extracted other parameters such as audio and video bitrates, number of frames, and stream sizes from sample files via the Media Info Metadata Extraction tool [22].

To quantify the results, two distinct objective measures of QoE are used, namely the Video Quality Metric (VQM), given by equation 3and the Structural Similarity Metric (SSIM), given by equation 4 [23]. Zero scores in the VQM metric means the best possible quality, everything else has some degree of degradation. On the other hand, the SSIM metric has a scale from zero to one, where values closer to one are better. It's important to note that VQM tends to be more stringent with video artifacts. This results in poorer scores, even for video footage with a reduced number of defects. This trait is more evident when comparing the mechanisms with the baseline, which produces larger differences.

$$VQM = \frac{1}{1 + e^{0.17\times(PSNR - 25.66)}} \quad 10 \leq PSNR \leq 55 \tag{3}$$

$$SSIM(x,y) = [l(x,y)]^{\alpha}[c(x,y)]^{\beta}[s(x,y)]^{\gamma} \tag{4}$$

All evaluations are carried out with the MSU video quality measurement tool [24]. Table 4 summarizes the common SSIM and VQM scores, additionally because of the network footprint of all experiments. The results validate the proposed mechanism, which outperformed all its competitors. In the end, the SETV mechanism enables increasing the perceived video quality while downsizing the network overhead in urban and highway scenarios. This is attributed knowing that the proposed mechanism only adds the required amount of redundancies to the foremost important video parts.

Table 4. Average SSIM, VQM and network overhead

	SETV	ShieldHEVC
Urban environment		
SSIM	0,924	0,839
VQM	1,680	2,790
Overhead	24,555%	32,778%
Highway environment		
SSIM	0,902	0,822
VQM	1,184	2,032
Overhead	21,777%	30,555%

5. Conclusion and perspectives

Due to the ever-increasing video transmission, especially with the exponential availability of connected cars and therefore the emergence of recent technologies like self-driving cars, the necessity for a QoE-based and network-sensitive mechanism to shield video transmissions is more and more noticeable. During this context, the proposed SETV mechanism can protect the foremost QoE sensitive data against network disturbances. This adduces adaptable video transmission over networks with error-prone characteristics and ensures in higher QoE for end-users. Through a comprehensive set of experiments, the SETV identifies the video and network characteristics that have a serious impact on quality. Further, by using these details within the "decision-making" process, it provides both superior qualities of service and efficient management of wireless channel resources. In future work, a special set of mechanisms, mobility scenarios, and environments will be implemented and evaluated. Additionally, other parameters associated to the network will be used to test using a bench implementation with real equipment and vehicles.

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