Adaptive QoE-driven Video Transmission over Vehicular Ad-hoc Networks

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***Abstract*—Vehicular Ad-hoc Networks (VANETs) are envisioned to offer support for a large variety of distributed applications that range from alerting drivers to autonomous driving features and video services. The use of video-equipped vehicles, with support for live transmission, unveils the need for an adaptive Quality of Experience (QoE)-driven mechanism to overcome several challenges and provide a good video quality. These challenges can range from the scarce network resources and vehicles movement to the time-varying channel conditions and high error rates. Adaptive Forward Error Correction (FEC) schemes can be tailored to shield the video transmission with QoE assurance. The adaptive QoE-driven and FEC-based mechanism proposed in the paper safeguard real-time video transmissions over high-mobility and error-prone networks, improving both the usage of resources and the user experience. Benefits and footprint are evidenced through experiments and QoE assessments. The results demonstrate that the proposed mechanism is able to outperform both non-adaptive and adaptive competitors.**

***Index Terms*—Motion intensity, Forward Error Correction (FEC); VANETs; Fuzzy Logic; Quality of Experience (QoE); Unequal Error Protection (UEP)**

I. INTRODUCTION

The safety and efficiency of modern transport systems have been improved with the recent development of the Intelligent Transportation Systems (ITS) applications. The Vehicular Ad-hoc Network (VANET) is the core component of the ITS and offers support to a wide range of video services. This growth is linked to several improvements on both network and video technologies, as well as with the high demand for this type of content [1].

The adoption of video services can be helpful in a wide variety of situations, such as driver awareness, traffic status, and road safety, as well as business or entertainment applications. However, the unreliable wireless connection of VANETs imposes a number of drawbacks ranging from the high mobility of the nodes to the error-prone communication channels [2]. Although video services are better at conveying a message, by providing information with higher precision, it is essential to protect the video delivery against losses [3]. This unveils the need for an adaptive mechanism to improve the video transmissions allowing better Quality of Experience (QoE) for the end-users.

The QoE can be described as the measurement of the overall level of end-user satisfaction with a service, which is related to, but differs, from the well-considered concept of Quality of Service (QoS). An efficient QoE-driven mechanism for live video distribution is one of the main challenges in VANETs [4]. This mechanism has to use a proper video quality adaptive control considering the QoE, the video details, and the intrinsic network characteristics to enhance the video quality, while saving resources.

Several techniques to improve the video quality have been proposed. A number of them rely on adapting the routing protocol. An efficient and reliable routing protocol will provide a large impact on the video quality, however, the improvement will only go up to a certain point, after that, it is necessary to add redundancy to maintain or even increase the video quality level in wireless environments. In order to provide redundancy, Forward Error Correction (FEC) techniques have been used successfully in live video transmission [5]. Due to the limited and oftentimes unfairly distributed wireless channel resources, an adaptive FEC-based mechanism is desirable to produce less network overhead, while increasing the human perception of live video flows.

In the light of the aforementioned challenges, this paper proposes an adaptive QoE-driven COntent-awaRe VidEo Transmission opTimisation mEchanism (CORVETTE) to improve the resilience of video transmissions over VANETs. One common issue found in the existing mechanisms is the lack of QoE-awareness. Because of this, important video characteristics, from the human perspective, are neglected, resulting in unnecessary redundancy. To tackle this issue, the CORVETTE uses a Hierarchical Fuzzy System (HFS) to add a precise amount of redundancy exclusively on QoE-sensitive data. This ensures high-quality video transmission while downsizing the network overhead. The CORVETTE mechanism was assessed through objective QoE metrics, by using real video sequences and actual maps' clippings.

The remainder of this paper is structured as follows. Section II describes the related work. The CORVETTE is shown in Section III, and its assessment is presented in Section IV. Conclusions and future work are given in Section V.

II. RELATED WORK

In the last few years, several FEC-based solutions have been proposed to improve the video quality over VANETs. The Blind XOR (BXOR) solution [6] enhances the video transmission through the use of a low-overhead XOR redundancy algorithm. In this proposal, a set of packets is

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blindly retransmitted, even if they had not been lost, based on the conditional reception probability (CRP). The CRP is estimated on the server node without any feedback from the clients. One of the weaknesses of this mechanism is that it only uses CRP and there is a lack of accurate CRP models in the literature. Additionally, the BXOR does not consider the video characteristics. These details are known to have an impact on the natural video resilience against packet loss, and consequently, on the video quality for end-users.

The Hybrid Video Dissemination Protocol (HIVE) [7] multi-layer approach combines node selection technique, traffic congestion control mechanism, and application layer erasure coding scheme to improve the quality of video transmissions. This combination allows avoiding high packet collisions, keeps a low latency, and increases the packet delivery ratio. The authors claim that HIVE improves the QoE for the end-users, however they rely only on the Peak signal-to-noise ratio (PSNR) metric, which is known for not providing a good relation between its results and the human vision system. Moreover, this proposal also does not consider video characteristics.

Another optimization proposal compares the utilization of Random Linear Coding (RLC) and XOR-based coding to improve video quality [8]. The authors show that using either erasure coding it is possible to have a successful increase on the reception of video packets over error-prone networks, however the XOR-based coding outperforms the RLC. This study is heavily based on finding the optimal packet block size leaving out important details about the video characteristics and network status.

III. QoE-DRIVEN VIDEO TRANSMISSION

Owing to the open issues aforementioned, particularly the shortage of adaptive QoE-driven mechanisms that efficiently consider the motion activity of the videos together with VANETs features, this work outlines and evaluates an adaptive QoE-driven COntent-awaRe VidEo Transmission opTimisation mEchanism (CORVETTE). The mechanism provides higher QoE during the video transmissions over VANETs without unnecessary network overhead. The proposed mechanism enhances our previous work [9] and the main improvements are described next.

A. CORVETTE architecture

Fig. 1 shows the overall procedure of our mechanism. First of all, the network status (1) is estimated. Several parameters are used, such as the network density, which is computed using the convex hull area and the number of 1-hop nodes. Furthermore, the Packet Loss Rate (PLR) and the node's position are also considered. After that, using cross-layer techniques, crucial details about intrinsic video characteristics are gathered (2). This includes the motion vectors, image resolution, frame type and size, as well as macroblock (MB) details. Once they are loaded in the fuzzy interface engine, it is possible to compute a suitable amount of redundancy for each packet (3).

In order to keep an up-to-date network status, this information is reassessed at every intermediate node (4). Additionally, to rule out the necessity of performing processor intensive tasks, such as deep packet inspection, on each and every packet, the video details are already embedded in each packet header at the server node. The hop-by-hop IPv6 optional header field was used to this end. In other words, it just needs to be read and it is ready to use (5). This enables the ability to adjust the amount of redundancy on each hop (6). At the end (7), a video with high QoE is delivered to the users.

B. Into the design of CORVETTE

As mentioned before, the CORVETTE mechanism is comprised of several process and modules that are going to be detailed in this section. First of all, to enable the CORVETTE real-time execution, a knowledge database has to be created using a hierarchical clustering technique [10]. This database stores information regarding the relationship between a number of video characteristics and their impact on the QoE. A detailed explanation of this can be found in [9]. Resorting to both the knowledge database and human expertise several fuzzy sets and rules can be defined. After this analysis, all the generated data can be loaded in the fuzzy interface engine and it is ready to be used in the real-time mechanism. This is an imperative phase considering that a few variables will be handled in real-time, allowing thus, a more accurate and at the same time, a faster mechanism.

The CORVETTE mechanism adopts Fuzzy Logic (FL) to build a comprehensive and dynamic scheme. Through FL it is possible to take into consideration several network and video characteristics and even then be fast enough to run in real-time. However, on standard FL systems the number of rules increases exponentially depending on the number of variables. One way to address this problem is by using a Hierarchical Fuzzy System (HFS), where low-dimensional fuzzy systems can be arranged in a hierarchical form. This allows reducing the global number of rules by only growing linearly.

Fig. 2 shows the several hierarchical levels used by CORVETTE. The output of each low-level component in the previous layer is used as input to the next layer components. As mentioned before, on each network hop the amount of redundancy is adjusted according to several factors, such as the network density, the PLR, and the distance to the next hop (or final destination). This operation is represented by the (A) portion of the HFS structure. On the other hand, at the server node, the full HFS structure is performed, which is composed of the (A) and (B) parts.

In the same way as in standard FL schemes, the design of HFS also involves the definition of several fuzzy components, such as the rules, sets, and membership functions. Since this is a complex process, it has to be executed offline and only once. After loading all the generated information into the fuzzy engine, it can be used on-the-fly and with a high performance.

B.1. The "General Network" layer conception

The "General Network" components are the "Network status" and the "Communication surroundings". The former is given by the combination of network density and PLR, and the latter is the position of the vehicles. To compute the network density, the number of nodes is divided by the

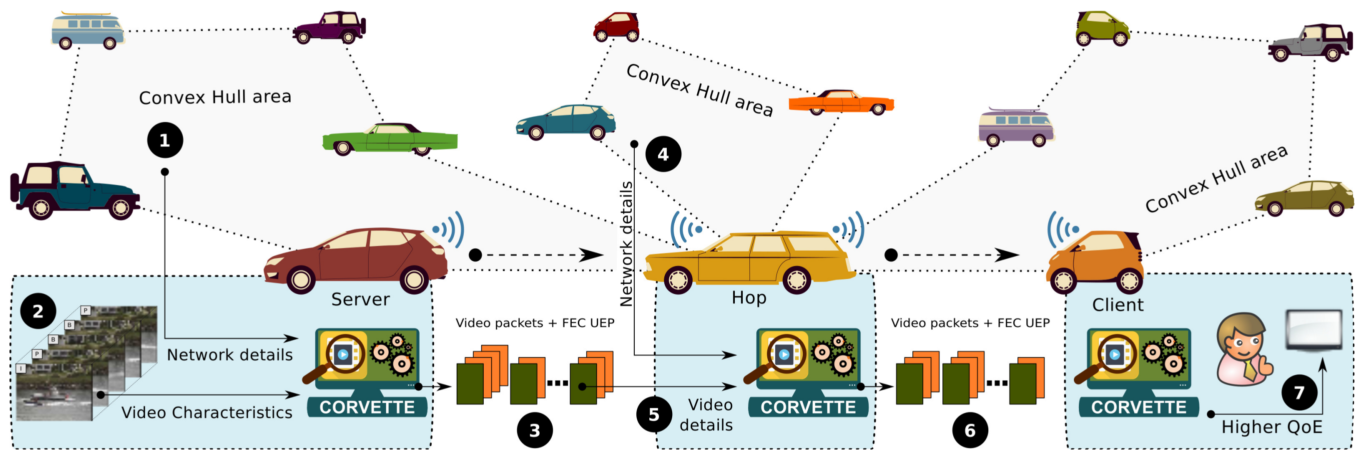

Fig. 1. General view of the CORVETTE mechanism

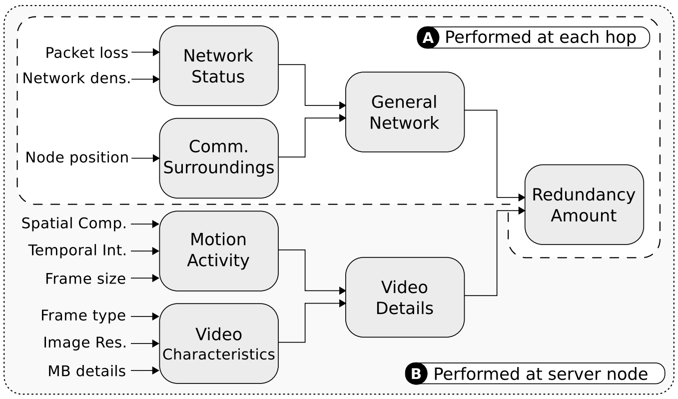

Fig. 2. Hierarchical Fuzzy Logic structure

network area. Because there is no fixed structure on VANETs and they can quickly change over time, it is challenging to estimate the network surface area. To solve this problem, our mechanism uses a convex hull algorithm. In this type of algorithm, a convex polygon is drawn including all the nodes on the network. A polygon is convex when it is non-intersecting and a segment between any two points on the boundary lies entirely inside of it. Successively, a convex hull is the smallest polygon containing all the points.

The QuickHull method was chosen because it uses a divide-and-conquer algorithm. In this approach, it is easier to find the convex hull of small sets, and at the end, the discovered hulls are merged. Once the convex polygon is found, it is possible to calculate the surface area and use it to find the network density.

Another component of the "Network status" is the PLR. The main goal in defining this parameter is to identify the impact of different PLRs in the QoE. It is well-known that video sequences have a natural resiliency to packet loss [11]. To better define the PLR category, a broad number of network simulations with a large number of video sequences were carried out. The results show that the QoE is good from the PLR 0% up to 11%. Additionally, in most of the cases, from 5% as far as 22% a tolerable video quality for end users was noticed. When exceeding 17%, however, a quick decrease in the video quality was observed, especially in high motion intensity videos. The majority of the cases, over 34% of PLR, the QoE became unbearable. Using FL it is possible to create classes of PLR exactly as found in the experiments, even with overlapping values. Algorithm 1 shows the PLR set defined through the aforementioned results.

Algorithm 1: Packet loss rate input set

```
InputLVar* PLR = new InputLVar("PacketLossRate");
    PLR → addTerm( TriangularTerm("LOW", 0, 11));
    PLR → addTerm( TriangularTerm("MEDIUM", 5, 22));
    PLR → addTerm( TriangularTerm("HIGH", 17, 100));
engine.addInputLVar(PLR);
```

The last component of the "General network" layer is the node position. Nodes that are far away tend to need more redundancy to keep a good video quality, due to greater radio-frequency interference and signal attenuation. Moreover, the position information can be very valuable when combined with the network density and the PLR. For instance, if a node is far away in a very dense network, it will need much more redundancy than if the network was not heavily populated.

B.2. The "Video Details" layer conception

Besides the network characteristics, the video details also play an important role when defining the amount of redundancy needed for each video sequence. In the CORVETTE HFS the "Video details" layer is composed of the "Motion activity" and "Video characteristics" components.

Firstly, the motion activity will be quantified. This parameter is given by the combination of the spatial complexity and temporal intensity. The spatial complexity represents how much static information the next frame has in comparison to the previous one; it includes the colour, and luminance saturation as well. Using the Sum of Absolute Differences (SAD) [12] it is possible to compute this difference, however, it compares each pixel from both frames making it a very complex and time-consuming operation. Because of that, the CORVETTE mechanism uses the normalized frame size to define this parameter. In doing that, it is able to perform quickly and allows the use of arbitrary video resolutions.

Once all the information is normalized, a hierarchical clustering is performed, and the clusters are divided in "small", "medium", and "high" spatial complexity according to the link distance between them [13]. As soon as the set is defined, a membership function needs to be associated with it. This is a complex and problem-dependent task proving difficult to come upon an optimal solution [14]. Because of that, piecewise linear functions are desirable. These functions are formed of straight-line sections, providing both simplicity and computationally efficient operations.

As aforementioned, another parameter employed to quantify the magnitude of the motion activity is the temporal intensity. Motion Vectors (MV) details are used to characterize the intensity because they describe the transition of objects on a plane. The MPEG standard describes them as the movement of macroblocks (MB) from one location in a given frame to another location in the next one. To enable the capability of comparing video sequences with distinct MB sizes and resolutions, the CORVETTE mechanism uses the MB area, which is translated as how many pixels are being moved.

Additionally, the Euclidean distance pointed by each MV is computed. This gives the exact information of how far the MBs are being moved by a specific vector. As the same as before, all the information is normalized and clusters are created. However, as a result of the exploratory analysis was found that five clusters would better represent the temporal intensity. They are "very low", "low", "medium", "high", and "very high", as showed in Fig. 3.

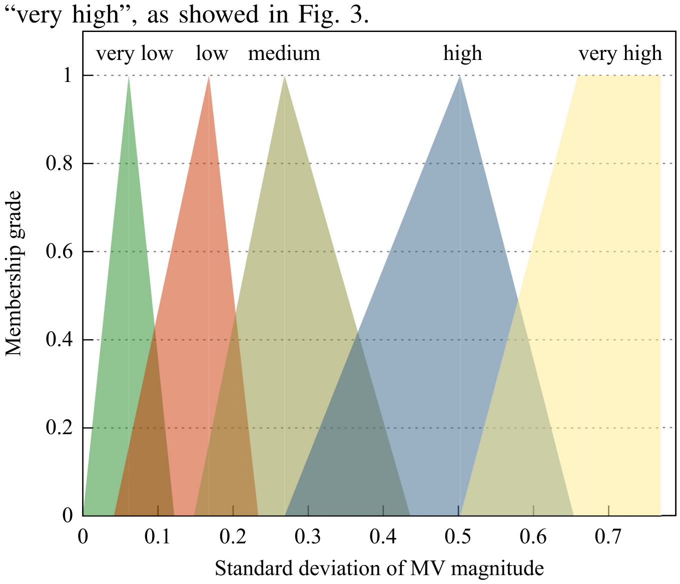

Fig. 3. Temporal intensity membership function

After defining all fuzzy sets, it is time to create the fuzzy rules. This task requires a combined expert knowledge on video characteristics, network details, and VANETs properties. Since the CORVETTE mechanism adopts an HFS, the rules need to be designed in layers. This layered system allows reducing the complexity of making them, because there are fewer input variables to be considered at the same time.

With all the fuzzy sets and rules outlined, they are ready to be loaded in the Fuzzy Logic Controller (FLC) and be used in real-time. The construction of this offline process has to be fulfilled just once. This enables the FLC to determine the better-fitted amount of redundancy to each video sequence on-the-fly in a VANET environment.

IV. Performance Evaluation and Results

The main goal of the CORVETTE mechanism is to improve the QoE for end-users. At the same time, it avoids unnecessary network overhead, preserving wireless resources.

A. Experiment setup

The experiments were performed in the Network Simulator 3 (NS-3). The simulated scenario is composed of up to 360 vehicles, using IEEE 802.11p Wireless Access for Vehicular Environments (WAVE). The speed range varies from 5 to 17 m/s. Several real video sequences with three distinct resolutions (1080p, 720p, and SVGA) were used in the experiments. The videos are examples of regular viewing material, covering different content and distortions. These sequences also include still and cut scenes, colour and luminance stress, as well as several motion intensities. They were all encoded with H.264 codec and GoP length of 19:2.

Using the OpenStreetMAP, a clipping of 2 by 2 km of the Manhattan borough (New York City) was obtained. This clipping was used as input for the Simulation of Urban MObility (SUMO), which considers the map structure, driving patterns, routes, crossings, roundabouts, traffic lights, to generate the mobility traces, which were used in the NS-3 simulations. All communications are Vehicle To Vehicle (V2V). This technology is contemplated as the next generation of the connected cars. It does not require a pre-existing infrastructure and works like a mesh network, where each vehicle can send and receive information.

The adopted routing protocol is the Cross-Layer, Weighted, Position-based Routing (CLWPR) [15]. As the name implies, this is a position-based routing protocol that uses mobility information from the nodes to tailor itself for VANETs environments. Receiver nodes are using Frame-Copy error concealment; this means that if a frame is lost, the last good one will take its place. Table I recollects the simulation parameters.

TABLE I
SIMULATION PARAMETERS

PARAMETERS	VALUE
Display sizes	1920x1080, 1280x720, and 800x600
Frame rate mode	Constant
Frame rate	29.970 fps
GoP	19:2
Codec	H.264
Container	MP4
Propagation model	FriisPropagationLossModel
Mobility	SUMO mobility traces
Routing protocol	CLWPR
Wireless	IEEE 802.11p (WAVE)
Radio range	250-300m
Internet layer	IPv6
Transport layer	UDP
Location	Manhattan borough (New York City)
Map size	2.000 m x 2.000 m
Vehicles speed	18-61 km/h (11-38 mph)

Five distinct mechanisms were simulated as stated next: (1) Without FEC, to be used as a baseline; (2) Video-aware Equal Error Protection FEC (VaEEP), where I- and P-frames are equally protected; (3) Video-aware Unequal Error Protection FEC (VaUEP). This mechanism protects I- and P-frames with a specific amount of redundancy according to the importance of each one; (4) our previous adaptive FEC-based mechanism (AdaptFEC), which takes into consideration several video characteristics and the network state [13]. At last, (5) our novel CORVETTE mechanism.

B. QoE assessment

Fig. 4 shows the Structural Similarity Metric (SSIM) results. This objective QoE metric reflects the human visual system perception [16], where values close to one represent better QoE. The first thing to be noticed, is that when the simulation is performed with a small amount of vehicles, e.g., 40, the network is sparse and suffers from connectivity issues. The CORVETTE mechanism proves that it can handle those situations by adjusting the amount of redundancy correctly, thus, outperforming competitors. It is also important to perceive that the standard deviation is high in all mechanisms. This can be expected since some video sequences tend to be naturally more resilient to packet loss than others, resulting in distinctive quality scores. This is especially true in low motion intensity videos. On the other hand, when the network is very dense, e.g., above 300 cars, the mechanisms have to deal with interference and a degraded network connection. Here again, the CORVETTE surpasses the other mechanisms, providing better video quality. All things considered, the proposed mechanism exceeds by 48% the without FEC scheme when it comes to video quality. Against VaEEP and VaUEP schemes, the CORVETTE mechanism granted over 23% and 19% better scores, respectively. In comparison to AdaptFEC, the proposed mechanism assured more than 11% higher video quality. At first, this value does not seem to be very high, however we were able to achieve it while adding 41% less network overhead.

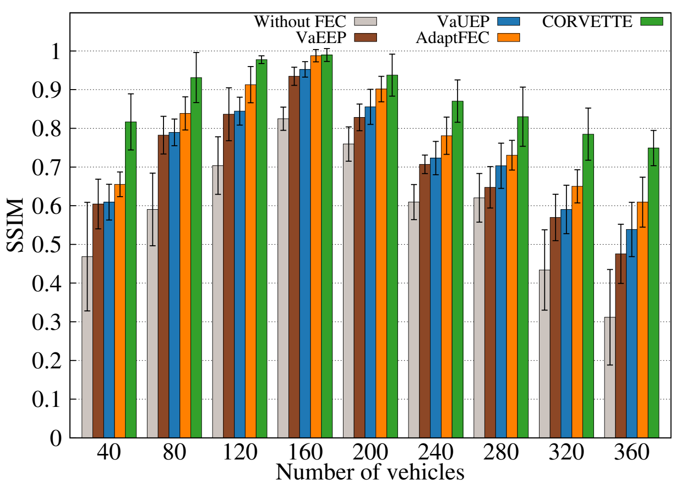

Fig. 4. Average SSIM for all scenarios

Fig. 5 presents the VQM scores. In this metric, values closer to zero stand for better quality videos. Another difference in this metric is that it tends to be stricter with video impairments. This means that it will give worse grades for videos with a few flaws. Nevertheless, almost the same pattern found in the SSIM metric is also present here. When the network is sparse, the videos tend to have lower quality, especially without any FEC-based mechanism. The best-case scenario in our experiments is between 160 and 240 vehicles. In this range, the videos were transmitted with better quality. Similarly to the SSIM assessment, using VQM the CORVETTE also outperformed all other mechanisms. Once again, this proves that the transmission enhancements performed by the proposed mechanism lead to a better video quality for the end users. On average, the CORVETTE mechanism provided 65% better video quality than the scheme without FEC, 42% and 40% higher scores than VaEEP and VaUEP, respectively. Against the AdaptFEC scheme, the proposed mechanism presented 30% better results.

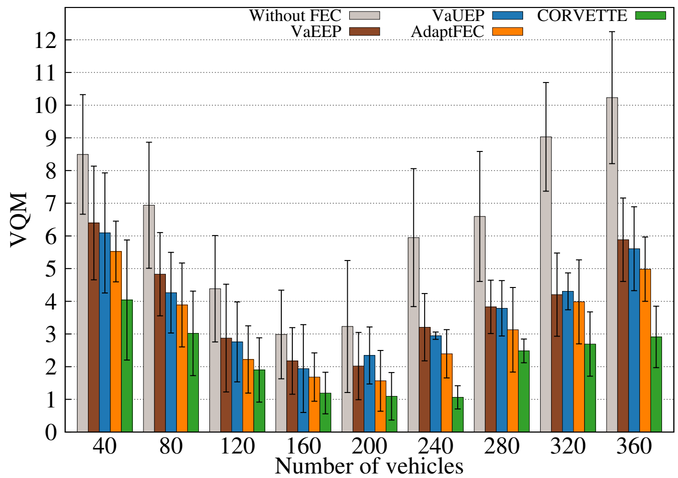

Fig. 5. Average VQM for all scenarios

C. Network assessment

Apart from higher video quality, a lower network overhead is equally desirable. This is especially important considering the scarce wireless resources as well as the unevenly distribution of the bandwidth. The network footprint is given by summing the size of all transmitted video frames minus the original frame size.

Fig. 6 shows the network overhead of all mechanisms. The VaEEP and VaUEP schemes are non-adaptive, thus producing a constant network overhead through the experiments. As can be seen in the graph, the non-adaptive protection schemes produce a large amount of network overhead, especially in the VaEEP case. The VaEEP protection is also not very efficient because it shields certain parts that do not require protection. Because of that, the VaUEP scheme takes into consideration the video characteristics, namely the frame type, and adds a specific amount of redundancy to each one. This grants the reduction of the network footprint while improving the video quality. Unlike the VaEEP, the VaUEP has a standard deviation because different video sequences require distinctive amounts of redundancy.

On the other hand, the adaptive mechanisms (AdaptFEC and CORVETTE) yielded better results in terms of network overhead, allowing a better usage of the network resources. Another important difference is the standard deviation, where the CORVETTE mechanism has higher values. In this case, this is very desirable, because it means that our mechanism was able to better identify the most important portions on the video sequences and protect them accordingly. This demonstrated a tailored protection, providing both superior video quality and low network overhead. On average, the CORVETTE mechanism added 41% less overhead than AdaptFEC. When compared to the VaEEP and VaUEP schemes, the proposed mechanism was able to generate 70% and 58% less overhead, respectively.

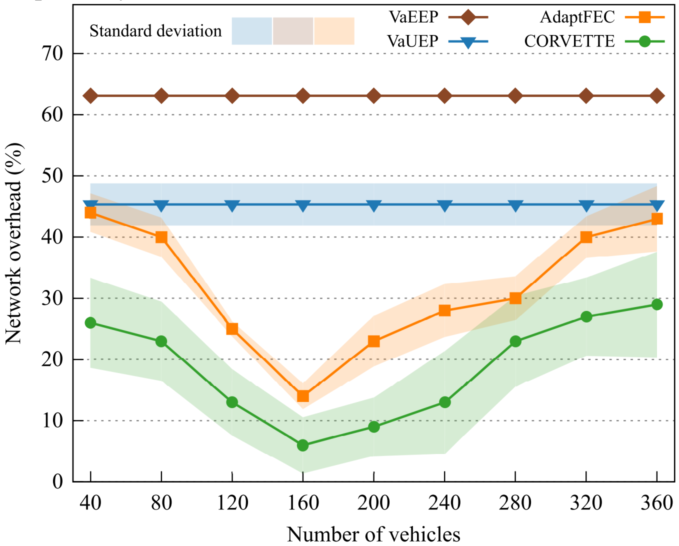

Fig. 6. Average network overhead

Table II summarizes the average SSIM, VQM, and network overhead scores. It shows that the CORVETTE mechanism was able to provide a substantial reduction in network overhead. This was possible by adding a specific amount of redundancy to each video sequences, and thus, avoiding any unnecessary redundancy. Additionally, it did so while increasing the video quality, leading to higher QoE for end-users.

TABLE II
AVERAGE SSIM, VQM, AND NETWORK OVERHEAD

	CORVETTE	AdaptFEC	VaUEP	VaEEP	Without FEC
SSIM	0,876	0,785	0,734	0,709	0,591
VQM	2,266	3,264	3,783	3,935	6,425
Overhead	18,777%	31,888%	45,342%	63,102%	–

Taking everything into consideration, the CORVETTE mechanism was able to perform an accurate motion intensity classification, which is used along with other video and network characteristics. The combined use of all this information enables the mechanism to add an adequate protection to each video sequence improving the quality for end-users.

V. Conclusion and Future Works

The growth of video delivery over VANETs highlights the demand for an adaptive QoE-driven mechanism to safeguard the transmissions against packet loss, and thus, keeping the user perception high. The CORVETTE mechanism improves the video quality over error-prone and high-mobility networks by protecting the most QoE-sensitive data. The results show that the proposed mechanism managed to precisely identify video and network characteristics to better protect the most important data, leading to a higher video quality and lower network overhead.

The results demonstrated that CORVETTE outperformed both non-adaptive and adaptive mechanisms in terms of video quality. In addition, our proposed mechanism was able to reduce the network overhead between 58% and 70% on average. In comparison to the adaptive FEC-based mechanism, our mechanism achieved between 11% and 30% higher QoE according to SSIM and VQM assessments, respectively. Additionally, the network footprint was 41% less, which means that an improved video quality was achieved without wasting the already scarce wireless resources. As future work, a different set of mobility scenarios is going to be evaluated as well as subjective QoE assessments.

Acknowledgment

This work was funded by the Brazilian National Counsel of Technological and Scientific Development (CNPq), FAPESPA, and also supported by the Intelligent Computing in the Internet of Services (iCIS) project (CENTRO-07-ST24-FEDER-002003), co-financed by QREN, in the scope of the Mais Centro Program.

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