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Efficient high-resolution video delivery over VANETs

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Abstract

The adoption of video-equipped vehicles in Vehicular ad-hoc networks (VANETs) is experiencing a rapid growth. It is also anticipated a substantial increase in the video content distribution with the arrival of self-driving cars as both passengers and vehicles will be able to produce and consume this type of media. This unveils a set of challenges, especially in VANETs where the network resources tend to be scarce and the connections suffer from time-varying error conditions. Taking everything into consideration, a Quality of Experience (QoE)-driven mechanism is desirable to enhance the video delivery over error-prone networks. To this end, the combined use of forward error correction and unequal error protection has proven its efficiency in delivering high-quality videos with low network overhead. The proposed intelligent quality-driven and network-aware mechanism (AntArmour) uses an ant colony optimization scheme to dynamically allocate a precise amount of redundancy. This allows AntArmour to safeguard, in real-time, the live transmission of high-resolution video streams. This operation is performed according to specific high efficiency video coding details and the actual network conditions such as the signal-to-noise ratio, the network density, the vehicle's position, and the current packet loss rate (PLR) as well as the prediction of future PLR. The experiments were performed using real map's clippings and actual video footage. The assessment was performed with the aid of two well-known objective QoE metrics, as well as the measure of the network overhead. The results showed that the proposed mechanism outperformed all its competitors in both video quality improvement and network overhead decrement.

Keywords VANETs · Forward error correction (FEC) · Unequal error protection (UEP) · High-resolution video · Quality of Experience (QoE)

1 Introduction

In the last few years, there has been a rapid proliferation of a wide range of real-time video services and applications, such as mobile social networks, multimedia streaming, and interactive gaming. This growth can be partly attributed to the recent development and improvement of mobile devices, such as notebooks, tablets, and smartphones [1, 2]. Furthermore, Vehicular Ad-hoc Networks (VANETs) are envisioned to offer support for a large variety of distributed applications such as road and traffic alerts as well as autonomous driving capabilities and video distribution. All these improvements allow an increased number of services and applications to be easily available to a large number of end-users. In addition, it is expected that self-driving cars will generate a large amount of data because of its hundreds of on-vehicle sensors, such as multiple cameras, sonar, radar, and Light Detection And Ranging (LIDAR). Although not all the generated data need to be shared in real-time, the video of multiple cameras could help improve several Advanced Driver-Assistance Systems (ADAS) such as take over and lane change decision process, as well as adaptive cruise control, blind spot monitor, collision avoidance systems, and intersection assistant. Because of that, the whole Internet, and

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especially the mobile end-users, are experiencing a considerable growth in traffic that is in part led by these novel real-time video services. According to Cisco, by 2021 the global Internet traffic will be times higher than it was in 2005. Just to put into perspective how big the video-related services are going to be, the video IP traffic will represent over 82% of the global IP traffic [3, 4].

It is expected, in the near future, a massive increase in mobile data traffic. This stems from the fact that a number of new applications such as immersive videos (360-degree) and ultra-high definition video, as well as virtual and augmented reality, will be made widely available to end-users. Just to give one example, by 2021 it is predicted that every second almost a million minutes of all types of video contents will be sent over the global Internet [4]. In addition, the adoption of Ultra Dense Network (UDN) will be imperative to meet the new requirements, especially in crowded cities and areas of high-traffic density.

In association with this, the growth of video-equipped vehicles, with support for live transmissions, unveiling both opportunities and challenges. For example, it can convey an accurate portrayal of an accident or a disaster for the first response teams. The result of this quick assessment is twofold as it allows reducing the reaction time, as well as it facilitates the decision of which approach methods to use. The challenge, however, is that these services have to deal with the unreliable wireless connections facing impediments that can range from the scarce network resources and vehicles movement to the time-varying channel conditions and high error rates [5, 6]. Taking everything into consideration, it is clear the need for a mechanism to protect the video delivery against these adversities [7, 8]. In order to overcome these challenges, a quality-driven and network-aware mechanism is desirable to better protect the video delivery with Quality of Experience (QoE) assurance.

The QoE method is related to the well-known Quality of Service (QoS) paradigm. The main difference is that the QoE metrics attempt to assess video quality based on the level of satisfaction of the end-user, whereas, the QoS if more focused on the network point-of-view. Due to the combination of the demanding video requirements and VANET's ever-changing network topology, there is still a scarcity of reliable QoE-driven and network-aware mechanism to improve the delivery of live video [9–12]. Any mechanism that aims to exceed these adversities has to consider a multitude of factors, which includes several video characteristics and network details. Only in this way, it will be able to accurately identify and safeguard the most QoE-sensitive data leading to a higher perception of quality by end-users.

Several attempts to improve the video quality over VANETs have been made in recent years. A number of them are relying on adaptive routing protocols to reduce the impact of the above-mentioned issues [13–17]. As expected, the use of a reliable and tailor-made routing protocol poses a noticeable influence on the process of enhancing the video quality. However, this enhancement is confined to a particular level. If it is desirable to improve or even sustain the video quality over this level some kind of error correction (EC) technique is required. EC methods allow rebuilding the original set of video frames in the occurrence of losses. A well-known EC approach is the Forward Error Correction (FEC) technique , which have been used for years and are able to produce good results in live video transmissions [18, 19]. Nevertheless, an intelligent FEC-based mechanism is desirable to avoid the waste of wireless resources with an unneeded amount of redundancy.

In the light of the aforestated issues, this article proposes an intelligent QoE-driven and network-aware mechanism to safeguard the transmission of high-resolution videos over VANETs using Ant Colony Optimization (ACO) named AntArmour. This new mechanism is an improvement of our previous works [7, 19]. The proposed AntArmour mechanism takes advantage of the ACO probabilistic algorithm [20], which is simulated according to the ant's behaviour, to solve computational problems in real-time. In order to provide an efficient mechanism several video- and network-related features have to be taken into consideration such as the packet loss rate, the network density, the node positions, the video codec type, the frame type, just to name a few. All these features are assessed by the proposed ACO-based mechanism leading to an unequal error protection (UEP). This means that only the most important video frames are going to be protected with a tailored amount of redundancy.

Furthermore, the AntArmour mechanism also exploits the new High Efficiency Video Coding (HEVC) characteristics. The HEVC codec is based on the ITU Telecommunication Standardization Sector (ITU-T) H.265 standard and it is foreseen to be the replacement of the largely adopted H.264 (ITU-T) or Moving Picture Experts Group (MPEG)-4 Part 10 (ISO/IEC). The HEVC standard promotes substantial improvements in the whole video coding and decoding process, especially in motion compensation, intra prediction, motion vector prediction, and coding efficiency. Another important enhancement is the addition of compute-efficient parallel processing methods, as well as the support for high-resolution videos [21].

The AntArmour mechanism was assessed with the aid of actual maps' clippings and real video footage using well-known objective QoE metrics. The rest of this article is organised as flows. The related work is presented in Sect. 2. Section 3 presents AntArmour and its assessment is given in Sect. 4. At the end, Sect. 5 provides the conclusions and future work.

2 Related work

Several mechanisms have been proposed in the last years to improve the video quality in transmissions over connected cars, more specifically in VANETs scenarios. One approach in trying to solve this issue is the adaptation of the routing protocol such as the QoE-based routing protocol for video streaming over VANETs (QOV) [15]. The QOV mechanism assesses in real-time the video quality through the Pseudo-Subjective Quality Assessment (PSQA) metric. This procedure is performed at the receiver node and then broadcast to all the neighbours using `Hello` packets. With this information, the routing protocol is able to choose the best available paths to deliver the video. Considering that VANETs tend to have high-mobility nodes and thus being very dynamic networks, the frequency of the PSQA announcements has to be fairly high. This could flood the network with an excessive volume of `Hello` packets. Additionally, this proposal does not cover any kind of EC-based technique. Because of this, it can only maintain the video quality up to a certain level.

Another technique to improve the reliability of the video transmissions in VANETs is to use an adaptive multi-objective medium access control (MAC) retransmission limit strategy [22]. The optimisation framework uses the Road Side Units (RSUs) packet transmission rate and channel statistics to do a fine configuration of the MAC retransmission features. Although this optimisation improves the performance of video transmission, the major concern is to downsize the playback freezes and lessen the start-up delay. These are important aspects of providing a high perception experience to end-users, however, they are not enough to secure a high QoE. Another disadvantage of the proposed mechanism is the use of only RSUs and two-hop communications. One of the major benefits of VANETs is to allow the vehicles to communicate directly between one another, eliminating the need for a previous-deployed infrastructure. Imposing such limitations hinders the applicability of the mechanism. Furthermore, it is not performed any kind of error correction leading to a limited improvement on error-prone networks.

There are also several proposed mechanisms in the literature that adopt error correction techniques to improve the quality of video transmissions over VANETs. One example is the optimised cross-layer FEC (OCLFEC) [23]. It uses Luby Transform to encode the data according to priority values, which are founded by computing the mean squared error of each frame. An additional error correction code, rate-compatible parity check (RCPC), is used to add cyclic redundancy check bits. Both correction codes were optimised for video transmissions over the VANET environment. Using cross-layer techniques, the GoP sequences are evaluated and different weights are attributed to each group of frames. The downside of this strategy is that it needs several optimisation phases, which are time-consuming. This leads to an increased delay and consequently degrading the QoE. The assessment process only takes in consideration QoS characteristics, which are known to not faithfully represent the QoE experienced by the end-users. Moreover, the OCLFEC mechanism leaves out of the decision-making process the network state and the video's motion intensity. These are important characteristics of any type of mechanisms aiming to safeguard the transmission of video sequences.

Other mechanisms that aim to enhance the video quality during wireless networks' transmissions were proposed based on XOR codes and Random Linear Coding (RLC) [24]. The results obtained through a set of experiments demonstrated that the adoption of either of the erasure codes can lead to video quality improvements, especially in high-error rate networks. However, the XOR-based coding had better performance than the RLC paradigm. To further improve the performance of the proposed mechanisms the optimal packet block size is computed, enabling it to add a precise amount of redundancy. In doing that it was able to deliver videos with better quality while downsizing the network overhead. In spite of that, the proposed mechanism does not take into consideration the network and video characteristics, which are known to be considerably relevant in these cases. Features like the video content, the codec type, and the actual packet loss of the network have great significance in the optimisation process to compute a precise amount of redundancy, which in turn will lead to better video quality and lower network footprint.

The Hybrid Video Dissemination Protocol (HIVE) [25] is another proposal which takes advantage of a multi-layer scheme to enhance the video quality. One layer of the HIVE mechanism is responsible for the traffic congestion control, another layer uses an optimised node selection strategy, and the last one applies an application layer erasure code. This combination grants a higher packet delivery ratio as well as low packet collisions and low latency. The outcome of the experiments showed a betterment in the PSNR inducing the authors to claim that a higher QoE for end-users was reached. However, there is not enough evidence of that as the PSNR scores are known to have a low correlation with the human vision system [26]. In addition to this, the proposed mechanism does not consider the video details. This information has a substantial importance to determine how resilient a video sequence is and how much protection it needs in case of network impairments.

The ShieldHEVC is a self-adaptive mechanism to improve the video quality in transmissions over VANETs [8]. This mechanism uses both video characteristics and network details in the process of finding the most suitable amount of redundancy. The video details assessed are the ones that have a greater impact on the QoE such as the frame type and the motion intensity, as well as the codec-related details. In regards to the network parameters, it uses the vehicle's position, the PLR and the SNR, as well as the network density. The assessment of the mechanism was performed using objective QoE metrics and the measurement of the network overhead caused by the additional redundancy. The outcome of the experiments demonstrated that ShieldHEVC was able to increase the resiliency of the video transmissions by shielding the most QoE-sensitive video parts. Nevertheless, one of the main disadvantages of ShieldHEVC is that it only considers the current PLR which can lead to a mischaracterization of the network status as the past PLR may not repeat (or remain the same) in the future.

3 QoE-driven and network-aware video enhanced transmission

Considering the aforementioned challenges, this work unveils and evaluates the intelligent QoE-driven and network-aware video enhanced transmission mechanism (AntArmour). There is a scarcity of QoE- and motion-aware mechanisms that are able to use a broad amount of network details in conjunction with specific video characteristics. Because of that, the proposed mechanism was tailored to grant the transmission of video with the uppermost quality, as well as to lessen the footprint of the network overhead. The AntArmour mechanism is an enhancement of our previous works [7, 19]. The new architecture, functions and key improvements are pondered below.

3.1 AntArmour overview

The AntArmour mechanism is composed of two phases. The first one is carried out offline and the second is performed in real-time. Fig. 1 depicts the offline phase. There are four steps in the offline phase. The first one (1) is to build a video database which has several real video sequences with different resolutions. The video samples also encompass a very diverse viewing content which represents commonly watched videos. Additionally, the sequences have colour and luminance stress, contain cut and still scenes, in conjunction with several distortion levels and diverse motion intensities.

Once the video database is fully assembled an exploratory data analysis is performed in the second step (2). This analysis supports the characterization of how distinct video sequences are distressed by both the arrangement of the network and the impairments introduced by it. In order to do that, several video sequences are assessed in a bundle of network configurations under different levels of disturbances. By analysing the results, it is possible to typify the QoE-related data which are needed to conceive the fuzzy sets and rules.

The third step (3) of the offline process is responsible for delineating the ACO specifics, i.e. the construction graph, the candidate list, and the heuristic values. The construction graph refers to the association of a set of QoE- and network-related parameters (e.g. motion intensity nodes, frame type and size nodes, as well as the packet loss rate nodes) with a set of vertices in the graph, meaning the connections between the nodes. Using the results of the exploratory data analysis it is possible to create an efficient construction graph. In addition, the candidate list is a set of the best-ranked options for each node, restricting the number of available choices that need to be considered in each and every construction step, thus improving the real-time performance. The heuristic information is a value attributed to all nodes and vertices in order to direct the ants to a better route, giving the ability to explore the problem-dependent conditions found in the data analysis.

The last step (4) is the consolidation of all of the developed solutions, which includes the ACO metaheuristic and the fuzzy logic components, to work together in real-time. This offline procedure is essential in order to provide a fast and precise execution. This is only possible because a reduced number of variables and activities needs to be handled in real-time.

Figure 2 provides a comprehensive view of the real-time process of the proposed mechanism. The first three steps are responsible for the video-related details. First of all, the video frames (1) are converted into packets to be transmitted over the network (2). After that, through cross-layer techniques, several QoE-related parameters referring to the video characteristics are gathered (3). All the information is analysed in the video-aware process of the AntArmour mechanism. This means that the characteristics of an arbitrary set of video sequences that is being transmitted, such as the image resolution, frame type and size, motion vectors, and Coding tree unit (CTU) structure can be mapped to the best-correlated features found in the offline process, giving the impact on the QoE if the information is lost, which in turns, allows adding a tailored amount of redundancy.

Thereafter, the network conditions are assessed (4). As a means of doing that, a set of parameters is considered together, such as the SNR, current PLR, PLR prediction,

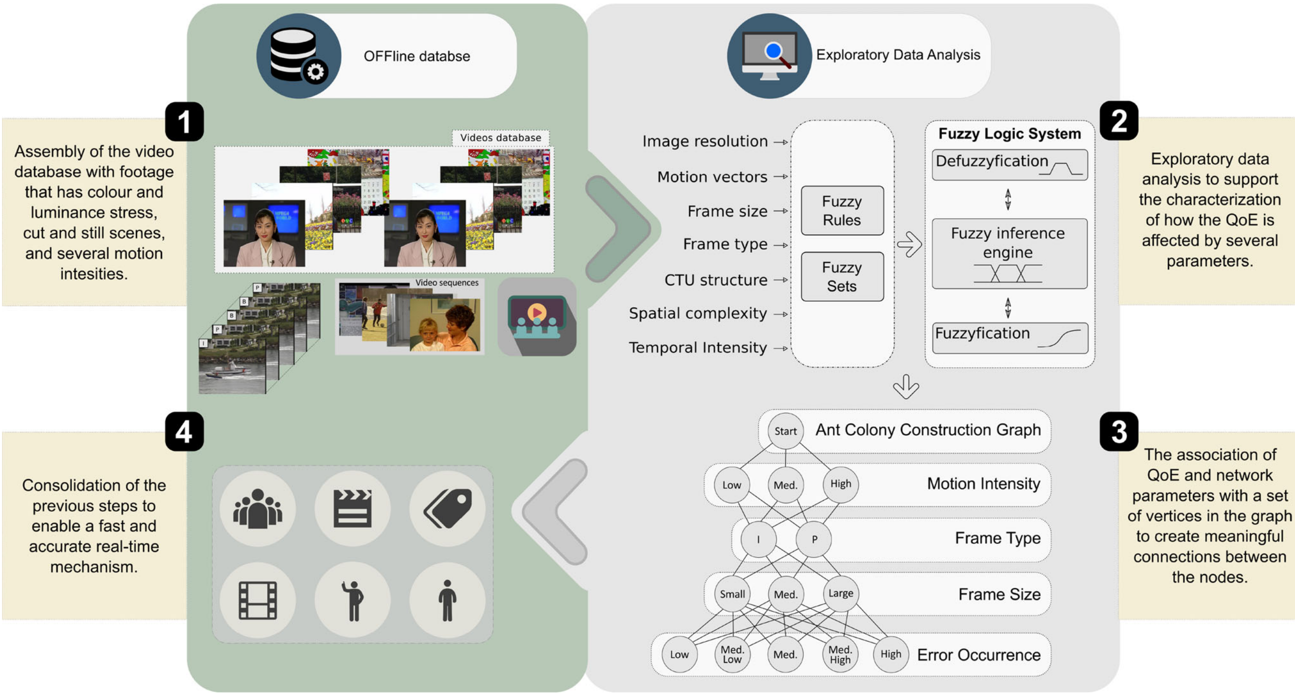

Fig. 1 General view of the offline process of the AntArmour mechanism

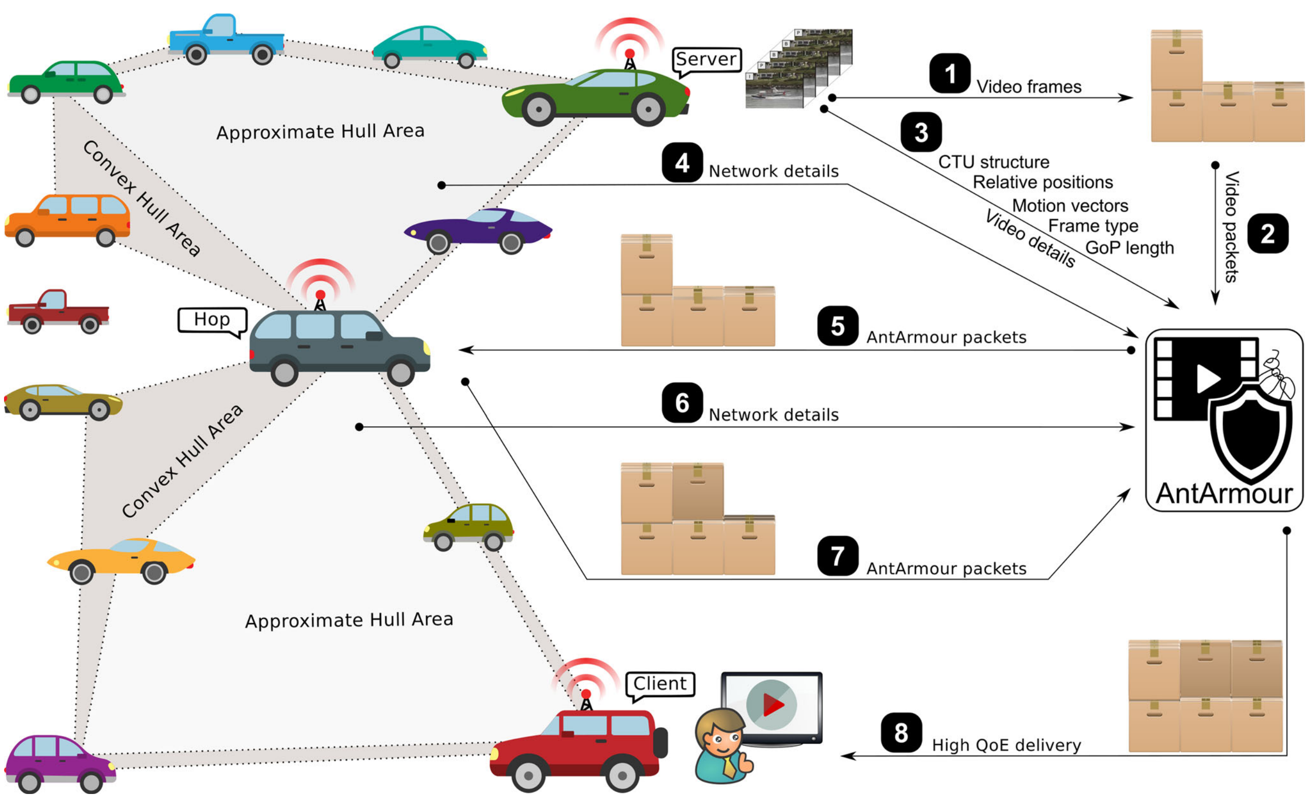

Fig. 2 General view of the real-time process of the AntArmour mechanism

and node's position, as well as the network density. In principle, none of the above-mentioned parameters by itself is accurate enough to define the network condition or the communication channels quality [27, 28]. However, with the combined use of all of them, it is possible to attain a highly accurate estimation of the network state. Following this, the decision-making module in the AntArmour mechanism is fed with all this information, which will allow it to compute the amount of redundancy to send along with the original video data, called AntArmour packets (5).

Taking in consideration that the network status may vary over time, and thus, diverge from one node (or hop) to another, the network condition parameter needs to be amended at each hop to accommodate this variation (6). Conversely, the video characteristics stay the same throughout the transmission. This condition is exploited by embedding all the QoE-related details in each packet header at the server node. In doing that, there is no need to run processor intensive tasks, namely deep packet inspection, on all packets at the intermediate nodes. To store this information the IPv6 optional hop-by-hop header was used [29], making it available whenever necessary. Because of this, the effort to adjust the amount of redundancy on each hop is reduced. At the end, the AntArmour mechanism is able to provide the end-users with high video quality improving the QoE (8).

3.2 AntArmour design

This section discusses the strategies and components of the AntArmour mechanism. As mentioned before, the proposed mechanism has an offline procedure which is the foundation for the real-time capabilities. One of the tasks of the offline process is to build a knowledge database using a hierarchical clustering technique [30, 31]. This provides the capability to retain several video characteristics along with the impact of each one on the QoE.

One of the main contributions of this work in comparison to the previous one is the joint use of ACO metaheuristic and fuzzy logic. The ACO is used to define all the mechanism's steps, from the characterisation of the video features to the network details. On the other hand, the fuzzy logic technique is responsible for handling all the abstract concepts. This combination allows building a dynamic and comprehensive mechanism. It also makes possible to quickly assess several video and network characteristics in real-time.

Another contribution is the enhanced offline process of the AntArmour mechanism and how the ACO metaheuristic settings are defined. This process underwent a complete overhaul and several optimisations were made to the ACO to ensure a fast and accurate real-time execution. Among these tasks are the building of the construction graph, the creation of the candidate list, the delimitation of the heuristic information, and the pheromone trails definition, which are described in detail below.

An additional improvement in AntArmour is the combined use of the current and the prediction of the PLR in the real-time process. In doing that, the proposed mechanism is able to better handle the network details as the wireless channel status can quickly change over time.

3.2.1 The "Construction graph" details

The construction graph is one of the principal elements of the ACO metaheuristic. It is used to map the problem under consideration onto a graph [32], so the feasible solutions are encoded as walks on the graph. This means that, as the ants traverse the construction graph, they construct a solution to the problem. In other words, the result value of the objective function in each walk corresponds to a viable solution to the original problem [33].

In order to better represent our needs, we are using a hierarchical graph as shown in Fig. 1 step (3). Because of this, once the ants start to walk they can only go to the next layer and always forward. Since it is only possible to move forward and from the previous to the next layer, the construction graph is not fully connected and the number of vertices is equal to the number of layers. Additionally, the distance between the nodes is directly proportional to the amount of redundancy required to improve, or at least maintain, a superior QoE. By taking this into consideration, the construction graph is built to better reflect this condition, enabling AntArmour to find the best possible solution for each scenario. Table 1 shows the adopted notation.

The resulting construction graph for this problem is described as a connection graph $G_c = (C, L)$, where nodes C are the components and L represents the set of partially connected components C, also called connections. The problem constraints are given by the function Ω and follow these conditions:

(1) In G_c, there is only one start node and it is located at the first layer;

Table 1 Adopted notation

Notation	Meaning
G_c	Connection graph
L_c	Candidate list
I_h	Heuristic information
arc (i, j)	Path between the i_{th} and j_{th} nodes
$I_{h(i)}$	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

(2) Let Q be the set of tours (complete walks) q in G_c which satisfy the conditions below:
   (i) q always starts at the start node of G_c in the first layer;
   (ii) q contains exactly one node of each layer of G_c;
   (iii) The last node on q belongs to the last layer of G_c;

Then Ω maps the set Q onto the collection of attainable solutions for this specific problem instance. Following this definition, the construction graph (G_c, Ω) gives the set of all feasible solutions. The construction graph refers to the association of a set of QoE- and network-related parameters (e.g. motion intensity nodes, frame type and size nodes, as well as the packet loss rate nodes) with a set of vertices in the graph, meaning the connections between the nodes. Using the results of the exploratory data analysis it is possible to create an efficient construction graph.

3.2.2 The 'Heuristic information' details

The heuristic information, also called heuristic value, provides the ability to exploit problem-dependent knowledge obtained prior to the execution or at run-time if retrieved from a different source other than the ants. This information will guide the ants' probabilistic solution, meaning that the ants have to take into consideration fewer options to decide how to move on the graph. In doing that, it will reduce the local search spectrum and consequently improve the solutions. Owing to this fact, the ACO algorithm is able to provide good performance in real-time.

Using the results of the exploratory data analysis, together with the knowledge database and human expertise, the heuristic information I_h is defined. This information is composed of the length $d_{(ij)}$ of the arc connecting the nodes i and j. Therefore, it is possible to define the heuristic information as $I_h = 1/d_{ij}$. As mentioned before, the length of the *arc* is directly proportional to the amount of redundancy required to improve or at least maintain a superior QoE. For this reason, the longer the tour the ants are walking the higher the redundancy amount needed. In the AntArmour mechanism, all the I_h are pre-computed once, at the bootstrap time. A table with all the possible values is generated, and it remains unchanged during the whole mechanism's run time.

3.2.3 The 'Candidate list' details

The candidate list is used to reduce the number of possible choices that have to be considered at every construction step. In order to accomplish such task, this list holds a small number of promising choices for next stop. The static lists are built based on prior knowledge of the problem, however, they can also be generated dynamically with information gathered on-the-fly. Since the proposed mechanism uses a hierarchical graph and it does not change over time, it can use a static candidate list composed of all the nodes of the next layer.

Let L_c be the candidate list of any specific node. An arc (i, j) is included in this list if the following conditions are met:

(1) The arc (i, j) it is not already included in L_c;
(2) The arc (i, j) establishes a connection from the source layer to a higher one, which means that it does not create cycles or backwards links;
(3) The arc (i, j) holds that $I_{h(ij)} > 0$, which implies that this connection needs to add some useful heuristic information;

The adoption of candidate lists is twofold. First of all, it restricts the walking path of the ants to certain conditions. This is of primordial importance to AntArmour due to its hierarchical graph design, and thus not allowing the ants to walk horizontally inside the same layer, but just between the layers. Secondly, it reduces the dimension of the search space of each ant, improving the real-time performance and therefore speeding up the process.

3.2.4 The 'Pheromone trails' details

The pheromone trails in the ACO metaheuristic help to guide the ants to make probabilistic decisions, and thus, construct possible solutions for the problem that is being solved. These trails are composed of numerical information distributed in the paths along the graph. During the algorithm's execution, the ants adapt the pheromone value to express their search knowledge.

3.2.5 The 'video characteristics' details

The video characteristics are an important aspect of defining a precise amount of redundancy. In AntArmour a fuzzy system was designed to represent these details. Fuzzy logic is a problem-solving methodology which focuses on how the general system should work instead of fully understanding its features. Because of that, it allows considering a large number of parameters while being fast enough to perform in real-time. Another advantage is the utilisation of fuzzy sets, which are related but differ from the classical sets, as they represent a degree of membership. This enables a more flexible and adjustable mechanism.

First of all, the AntArmour mechanism identifies three important video characteristics, namely CTU details, frame type, and image resolution. The CTU is a new H.265 component which replaces the old macroblock structure. It enables a more flexible arrangement of the data, which accommodates larger block structures as well as more subdivisions options, being especially useful to high-resolution videos. Several CTU details are taken into consideration, such as the size, type, and the number of subdivisions, to find how the video was encoded. This is helpful to compute the amount of redundancy needed by a specific scene to improve the QoE for end-users.

Another important parameter is the frame type. It is well-known that some frames are more important than others [34] on the video quality level. Because of that, it is important to identify the type of the frame that is being transmitted to add a redundancy amount compatible with it. The last parameter identified is the image resolution. This is needed to characterise the dimension of the video. This information is also used in correlation with the CTU details. Videos with a low image resolution tend to have a small number of large CTU blocks, whereas, videos with a higher resolution tend to have more large blocks.

In addition to the video characteristics, the AntArmour mechanism assesses the video's motion activity. This feature is composed of three parameters, namely the spatial complexity and frame size as well as the temporal intensity. The spatial complexity describes the difference of the static information from a given frame to another. In other words, how much a static scene is different from the next one. The use of the frame size helps to quantify this amount. The temporal activity is calculated from the motion vector (MV) details and portrays the motion amplitude in each video sequence. With the combined use of these parameters, it is possible to accurately classify the pace of action of a particular video sequence.

The joint analysis of all the above-mentioned parameters and human expertise provides enough information to build the fuzzy sets, rules, and the membership functions. The advantages of the fuzzy logic output are twofold. First, it helps to define the most suitable nodes in each candidates list (Lc) the ants will travel to. Second, as the output is not a crisp value but a degree of membership, this information is taken into consideration and only a proportional measure of the distance $d_{(ij)}$ is used to adjust the redundancy amount. For example, the frame size can be classified as $\{large, medium, small\}$, so the output of fuzzy logic would be $\{0.8, 0.2, 0\}$ for a given frame. This means that this particular frame belongs 80% to the *large* group and 20% to the *medium* one. As mentioned before, the total amount of redundancy is equal to the distance walked by the ants and since this frame only belongs 80% to the *large* group it will be considered only 80% of the distance $d_{(ij)}$.

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

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

3.2.6 The "network status" details

Along with the video details, the network conditions are also important. However, it is not a straightforward task the specification of what is a good or a bad channel as it is not possible to rely upon a single metric [27]. Because of that, the AntArmour exploits five distinct parameters to define the network quality status. The adopted metrics are the SNR, the actual PLR, the prediction of the future PLR, the network density, and the position of the vehicles. Each one of them is described next.

The SNR is a physical medium indicator usually used for spectrum sensing. It shows the signal level in contrast to the background noise level. By itself, this indicator is not a reliable measurement of the network quality as a strong signal will not always lead to an error-free network connection [27]. Nevertheless, a weak channel signal most probably will lead to a considerably low-quality connection. In order to build a more holistic indicator, the other metrics are also assessed.

The actual PLR tends to have a negative correlation with the SNR, which means that when one is high the other is low and vice versa. Furthermore, this indicator provides a network assessment closer to the application layer as the SNR is geared towards the physical spectrum. Thus, they are complementary to each other. However, the actual (or past) PLR is not enough to endorse future network behaviour. Because of that, the AntArmour mechanism also makes a prediction of the future PLR. There are a number of attempts to forecast the PLR using sparse basis models, time-series, and hidden Markov models. However, as the proposed mechanism needs to run in real-time, this prediction has to be easy and fast to compute. In addition to that, the main goal is not to create a highly accurate PLR prediction as this indicator is used together with the other parameters. With this in mind, the PLR forecast was computed using a weighted arithmetic mean.

In our case, a set of the five last PLR were used as input data, represented by $\{x, x_{n+1}, \ldots, x_5\}$. However, since our weigh input is normalised and the sum of all elements is always 1, the weighted arithmetic mean formula can be simplified as shown in Eq. 2.

$$a\bar{v}g = \sum_{i=1}^{5} w_i x_i \qquad (2)$$

The weight set adopted was found through several experiments and defined as $\{0.4, 0.3, 0.15, 0.1, 0.05\}$. There are three main advantages of adopting this procedure. First, it is precise enough to yield good results. Second, it follows the time-varying error characteristic of the wireless networks. And last, it is fast enough to run in real-time.

Another analysed parameter is the network density, which is computed by dividing the number of the vehicles by the total network surface area. It is a challenge to find this area because VANETs are highly dynamic networks without a centralised structure. The AntArmour mechanism addresses this issue by using the Bentley-Faust-Preparata (BFP) [35] approximation convex hull algorithm. This type of algorithm finds the smallest boundary polygon of all the nodes inside of it. The BFP algorithm is an approximation because it may discard a non-extreme point in a given strip even if it belongs to the convex hull boundary. However, the possible discarded point will never be too far from the boundary, making it a good approximation of the full convex hull.

Finally, the last parameter assessed is the node position. The distance between the nodes is important due to the radio-frequency interference and signal attenuation. Because of that, nodes that are far away from each other have a tendency to demand more redundancy to keep a high-quality video image. This is an elementary information but relevant to be used in association with the other input parameters.

4 Performance evaluation and results

The main goal of AntArmour is to improve the QoE for end users and at the same time prevent any nonessential network cost. The result is a meticulous use of the wireless resources while enhancing the video quality delivery.

4.1 Experiment settings

With the aim of performing an in-depth assessment of the AntArmour mechanism a couple of semi-detached environments were taken into consideration: the highway and the urban layouts. Each one of these geographic areas has a set of very singular traits, resulting in unique challenges.

The highway environment has the tendency to be an open space, thus comprising very few obstacles leading to a better signal propagation. Whereas, the urban geographic area has plenty of buildings, houses, and many other sorts of structures that will definitely disturb the wireless signal propagation. In addition, the mobility patterns are also fairly peculiar. On the highway, there are a small number of entrances and exits, with just a few driving options. On the other hand, at the urban area, there is an abundance of options, such as crossroads, streets, and avenues all nearby each other. The above-mentioned traits of both environments were well-tried in a collection of situations.

All the experiments were performed using the network simulator 3 (NS-3) [36]. The adoption of a network simulator offers a practical feedback which allows investigating the correctness and efficiency of the proposed mechanism in a controlled and reproducible environment. Therefore, it is easier to explore the unforeseen interaction between the multiple elements involved in the experiments [37]. In addition, it also allows a straight and fair comparison of results in a transverse manner among several research efforts. Despite the use of a simulator, real video sequences and traces of real network operations and characteristics were used. This provides closer results to real-world implementations.

The urban and highway environment share several experimentation features such as the network technology and the video-related characteristics. The Evalvid Tool [38] was used to send the video sequences encoded according to the H.265 standard. In order to experiment with a broad prospect, the videos had three distinct resolutions, namely 1080p, 720p, and SVGA. Additionally, for each resolution 10 real video sequences [39] were elected to enter the transmission process. The video sequences of the experiments were chosen in compliance with the recommendations of the VQEG [40] and ITU-T J.247 [41]. Which dictates what characteristics and how the video sequences have to be chosen to create a comprehensive QoE test set. They encompass distinct motions, still and cutscenes , as well as commonly viewing material. The pair sender/receiver are randomly selected and the video transmissions also begin at a random time. Different seeds were used to ensure distinct node positions and start transmission's times. At any given time, up to 30 videos are being exchanged simultaneously. A Frame-Copy error concealment is triggered at the receiver nodes in case of lost frames.

Besides the video parameters, both environments also have in common the same wireless standard, namely the IEEE 802.11p Wireless Access for Vehicular Environments (WAVE) [42, 43]. The communication mode was defined as Vehicle To Vehicle (V2V) to explore its infrastructure-less capabilities. This is an ad-hoc network allowing the direct communication between the vehicles, and it is anticipated as the next generation of connected cars. The adopted routing protocol was the Cross-Layer, Weighted, Position-based Routing (CLWPR) [44] because it uses the node's mobility-details to adjust the routes, as well as due to its position-based features.

Furthermore, mobility traces were used in order to have more pragmatic simulations. The Simulation of Urban MObility (SUMO) [45] was used to generate the traces from real map clippings. In doing that, it is possible to contemplate driving patterns, traffic lights, junctions, roundabouts, routes, and the number of lanes. The traces for the urban scenario were generated using an excerpt of 3.5 by 3.5 km of the Manhattan borough (New York City). This environment was populated with up to 450 vehicles with speeds varying from 20 to 60 km/h. The traces for the highway environment were produced using a cutting off of 15 km of the US Interstate Highway 78 (I-78). The environment was populated with the same number of vehicles, however, with speeds ranging from 80 to 120 km/h.

The adopted environments have some similarities but also some differences as the need for distinctive propagation models. The logDistance model was used in the highway experiments because of its small number of sources of interference as well as open spaces [46]. In the urban experiments, on the other hand, there are plenty of sources generating interference as well as plenty of obstacles. Because of that, the logDistance model by itself it is not enough to accurately represent this scenario. To produce a more realistic experiment the Nakagami-m propagation model was added on top of the logDistance model, supplementing the simulations with the fast fading characteristics which are consistently present in these scenarios [47]. Table 2 outlines the experiment's parameters.

The network and QoE assessments were performed with four distinct mechanisms plus one without any type of FEC, which is considered the baseline (Without FEC). In each case, both an urban and a highway environment were contemplated. The first scheme evaluated is a Video-aware Equal Error Protection FEC (VaEEP) mechanism, where I- and P-frames are evenly safeguard with a fixed amount of redundancy. The second scheme is a Video-aware Unequal Error Protection FEC (VaUEP) mechanism. It takes into account the different frame types to better protect the most important ones, in this case, the I-frames. The ShieldHEVC mechanism [8] was the third scheme tested and takes into consideration the codec type, network state, and several video characteristics. The fourth and last scheme is the proposed AntArmour mechanism.

Table 2 Experiment's parameters

Parameters	Value
Display sizes	1920×1080, 1280×720, and 800×600
Frame rate mode	Constant
Frame rate	29.970 fps
GoP	19:2
Codec	H.265
Container	MP4
Wireless technology	IEEE 802.11p (WAVE)
Communication	Vehicle to vehicle (V2V)
Routing protocol	CLWPR
Mobility	SUMO mobility traces
Radio range	250 m
Internet layer	IPv6
Transport layer	UDP
Highway environment	
Propagation model	logDistance
Location	I-78
Map size	15.000 m
Number of lanes	4
Vehicles speed	80–120 km/h (50–75 mph)
Urban environment	
Propagation model	logDistance + Nakagami-m
Location	Manhattan borough (New York City)
Map size	3.500 m × 3.500 m
Vehicles speed	20–60, km/h (12–37 mph)

4.2 QoE assessments

The adoption of objective QoE metrics is supported by the fact that they provide a measurable and verifiable video quality score. Another feature of these metrics is its unbiased traits. Since they are computed using mathematical calculations the motif of the video does not matter, only the quality level is assessed.

Not all objective QoE metrics, however, are known for producing reliable results that can be used to compare different video footage. Just to give one example, the PSNR is an objective metric based on a byte-by-byte comparison to assess data fidelity. Such procedure is only suitable to compare different mechanisms transmitting the same video. Additionally, this metric has a total disregard of what the data that have been transmitted actually represents. This means that the PSNR does not take into account the spatial relationship between the pixels and not even the pixel structure itself. Because of that, the visual importance of each pixel is disregarded [48] and it does not have a good correlation with the human vision system [26].

In order to quantify the results two distinct objective QoE metrics were used, namely the video quality metric (VQM) [49] and the structural similarity metric (SSIM) [50]. These metrics resemble the human visual system [51] on how the impairments are perceived by the end users. The score zero in the VQM metric means the better quality possible, anything else has some degree of impairment. On the other hand, the SSIM metric has a scale going from zero to one, where values closer to one are better. It is important to notice that VQM has the tendency to be more strict with the video artifacts. This results in worse scores, even to video sequences with a reduced number of flaws. This trait is more evident when comparing the mechanisms against the baseline, which will produce higher differences. All the assessments were conducted with the MSU Video Quality Measurement Tool [52].

Figure 3 depicts the SSIM scores of each mechanism of the urban scenario. There is a relatively small amount of vehicles in the first step (only 50) and this situation is reflected in the SSIM metric which gives considerable low scores, especially to the Without FEC, VaEEP, and VaUEP schemes. This can be explained by the lack of connectivity between the nodes as the video transmission is relying on only a few and scattered vehicles. In this same scenario, the AntArmour mechanism outperformed all the competitors by providing the video sequences with the highest quality.

In the urban environment, the SSIM scores increased almost 74% in comparison to the baseline. The best SSIM scores are reached when the network has between 200 and 300 vehicles. The experiments with these settings provided the best connectivity, covering the whole simulation area. At the same time, it also did not generate excessive interference, allowing the baseline scheme to achieve the best results. It is also possible to notice that when the network becomes denser (above 300 vehicles) there is a sharp decrease in the video quality, especially in the Without FEC, VaEEP, and VaUEP schemes. This can be credited to the increase on the PLR due to the communication interference among the nodes.

Figure 4 shows the average VQM scores for all mechanisms. As mentioned before, the VQM metric takes a stricter approach to quantify the video impairments. This

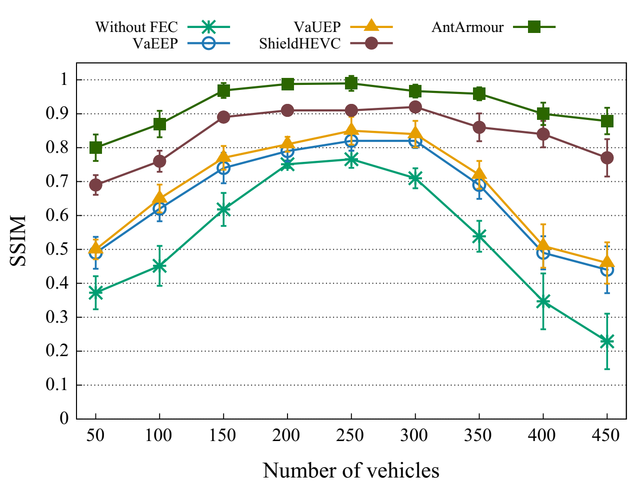

Fig. 3 SSIM assessment of the urban environment

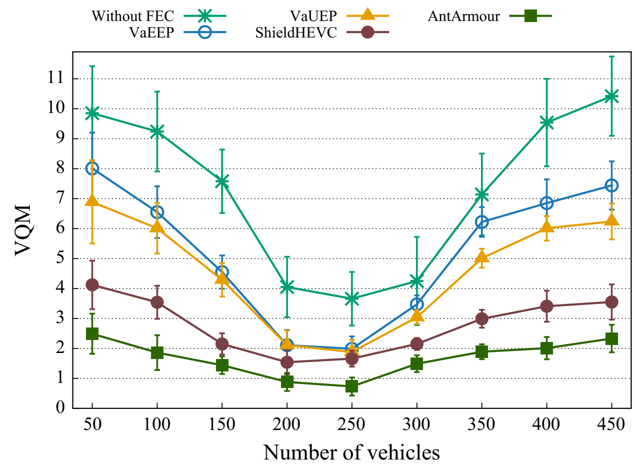

Fig. 4 VQM assessment of the urban environment

explains why the scores are higher than the ones given by the SSIM metric. Nevertheless, a very similar pattern can be found. At the start, when the network is sparse, the transmitted videos have low quality and are given bad VQM scores (high). After that, between 200 and 250 vehicles, the network has its better coverage, allowing to deliver videos with higher quality. The difference here between the SSIM and VQM assessment is that with 300 vehicles the SSIM scores are still considered as good as the VQM values are already starting to get worse grades. This again can be attributed to the stricter VQM evaluation process. Ultimately, the VQM scores had a reduction of 77% also against the baseline.

The highway environment was assessed with the same QoE metrics as well. Figure 5 shows the average SSIM scores for all mechanisms in the above-mentioned environment. A similar pattern found in the urban environment it is also present here. There are some connectivity issues, at the beginning, as the network is sparse, e.g., between 50

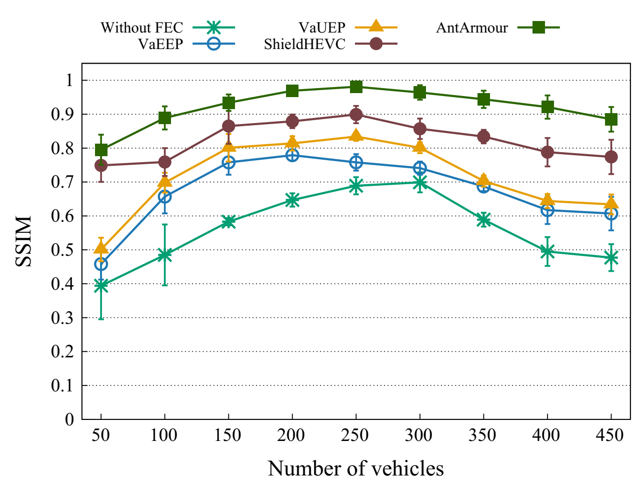

Fig. 5 SSIM assessment of the highway environment

and 150 vehicles. The best video quality was achieved when the simulated number of vehicles was between 150 and 300. All the assessed mechanisms scored above 0.7 which can be considered reasonable. The baseline was the only experiment which scored below this threshold. This is an expected result because no protection at all was added. Different from the urban environment, the highway scenario does not display a sharp decrease in the video quality with more than 300 vehicles. This can be attributed to the fact that the highway environment is not as harsh as the urban scenario. There is a lower level of interference hence the mild decrease in the SSIM scores. Once more, the AntArmour mechanism is able to surpass all its competitors with a SSIM increase of more than 63% in comparison to the baseline.

Figure 6 shows the average VQM scores for all experiments in the highway environment. The first thing to notice is that the values are closer together than in the urban scenario. This is additional evidence that the highway set-up is not as rough as the urban environment. In addition, all the scores portray an almost constant increase in the quality at the beginning, up to 250 vehicles, and likewise constant decrease towards the end. Nevertheless, AntArmour successfully overcomes all the competitors with a VQM improvement of over 74% when compared to the baseline.

4.3 Network assessment

Besides the QoE improvement, it is also desirable to lessen the network overhead. Figure 7 depicts the network footprint in both the urban and highway scenarios. Both non-adaptive schemes, namely VaEEP and VaUEP, produced a constant network overhead throughout the experiments. This happens because they have no adaptive functions that assess the network characteristics and actual status. The

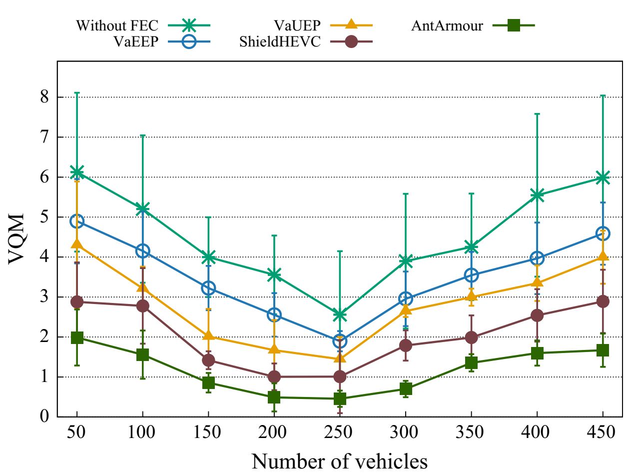

Fig. 6 VQM assessment of the highway environment

non-adaptive mechanisms add a fixed and rather large amount of redundancy. Since there is no network-related adjustment the large amount is needed to try to ensure the video quality. On the one hand, these mechanisms are simple and easy to implement, on the other hand, the protection offered by them is not particularly efficient. This happens because of their approach towards the way to add the redundancy. VaEEP safeguards equally all video data. However, not all video frames have the same need for protection. VaUEP tries to solve this matter by adding different amounts of redundancy to each frame type. The results show that with this procedure it is possible to reduce the network overhead while increasing the QoE.

The adaptive network-aware mechanisms, namely ShieldHEVC and AntArmour, achieved the lowest network overheads in both environments. It is possible to notice in Fig. 7(a) that when the network connectivity is better in the urban environment, such as between 200 and 300 vehicles, the overhead footprint associated with the redundancy mechanisms decreases. Another noteworthy result is when the network is very sparse (50 vehicles) or very dense (450 vehicles). On average, the AntArmour mechanism added between 25% and 68% less network overhead than its main competitors.

In the highway scenario, as depicted in Fig. 7(b), there is not a sharp decrease due to better network connectivity. This can be explained by the fact that the network conditions are more evenly distributed in the experiment as well as this scenario is not as harsh as the urban one. Notwithstanding, the best AntArmour results are obtained when the network is either very sparse or very dense. Here again, the proposed mechanism was able to cut down on the unnecessary network overhead, producing between 28 and 72% less footprint than its main competitors. This is the same pattern as the one observed in the urban environment.

Table 3 summarises the average SSIM and VQM scores, as well as the network footprint of all experiments. The overall results validate the proposed mechanism which outperformed all its competitors.

At the end, the AntArmour mechanism enables increasing the perceived video quality while downsizing the network overhead in both urban and highway scenarios. This can be attributed to the fact that the proposed mechanism only adds the necessary amount of redundancy to the most important video parts. A more detailed comparison between ShieldHEVC and AntArmour can be found in the next section.

4.4 AntArmour and ShieldHEVC side by side

To further highlight the AntArmour performance Fig. 8 shows the comparison of AntArmour and ShieldHEVC.

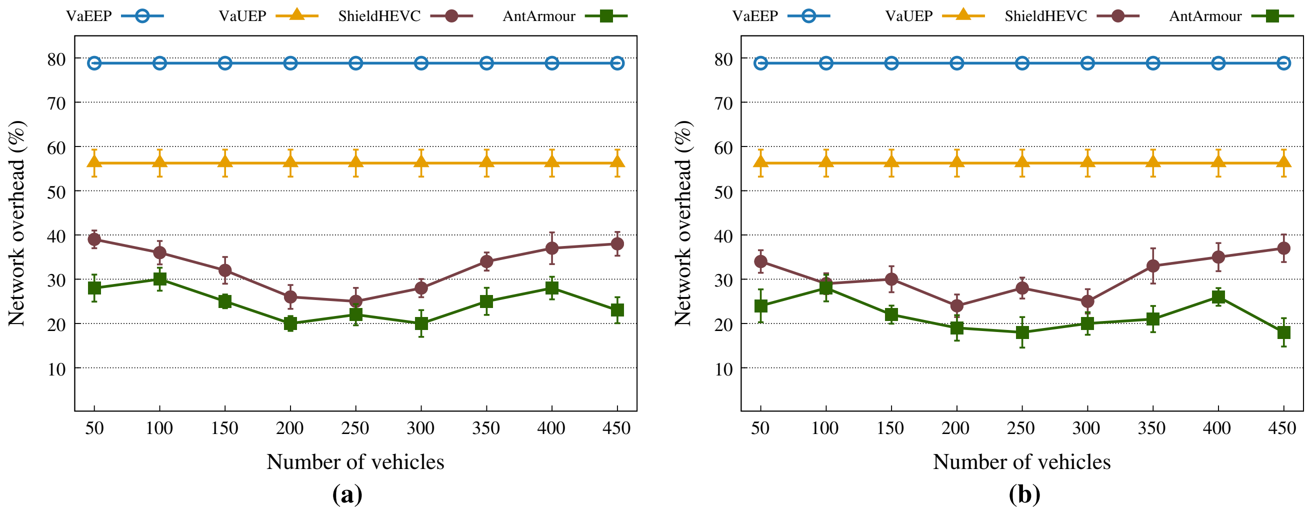

Fig. 7 Network overhead of all mechanisms. **a** Urban environment. **b** Highway environment

Table 3 Average SSIM, VQM, and network overhead

	AntArmour	ShieldHEVC	VaUEP	VaEEP	Without FEC
Urban environment					
SSIM	0,924	0,839	0,679	0,655	0,531
VQM	1,680	2,790	4,609	5,243	7,303
Overhead	24,555%	32,778%	56,230%	78,815%	–
Highway environment					
SSIM	0,902	0,822	0,714	0,673	0,562
VQM	1,184	2,032	2,848	3,531	4,567
Overhead	21,777%	30,555%	56,230%	78,815%	–

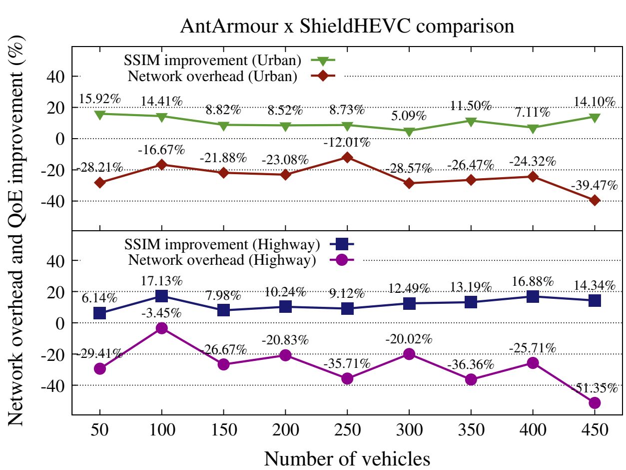

Fig. 8 QoE x network overhead

The first case depict the urban environment results and the second one the highway scenario outcome. Both graphs depicts the percentage of QoE improvement as well as the network footprint decrement. A positive percentage in the QoE assessment, which is desirable, means that our proposed mechanism improved the video quality. Differently, in the network assessment, a negative percentage is desirable, which means that our mechanism produced a smaller footprint.

In both environments, the AntArmour mechanism achieved significantly higher QoE scores while also reducing considerably the amount of network overhead produced. The percentage of QoE improvement in the urban scenario ranged from 5.09 up to 15.92%, with an average of 10.47%. At first these results seem rather narrow, however, it is important to notice that they were achieved against an already optimised mechanism. Along with the improvement in QoE scores, a 12.01–39.47% decrement in the overhead was also obtained. In other words, the AntArmour mechanism produced on average 24.52% less footprint than ShieldHEVC.

The results of the highway environment showed a similar tendency. The QoE improvement of AntArmour was between 6.14 and 16.88%, with an average of 11.94%. Here again, it is worth to remember that this comparison is against a specialised mechanism. The network overhead was reduced between 3.45 and 51.35%, with an average of 27.72%. These numbers support the claim that our proposed mechanism was able to deliver videos with higher quality, leading to a better user perception, as well as avoiding unnecessary network overhead.

5 Conclusion and future works

Due to the ever-growing video transmission, especially with the exponential availability of connected cars and the emergence of new technologies such as self-driving cars, the need for a QoE-driven and network-aware mechanism to safeguard the video transmissions is increasingly noticeable. In this context, the proposed AntArmour mechanism is able to shield the most QoE-sensitive data against network disruptions. This provides a resilient video transmission over networks with error-prone characteristics, leading to a higher QoE for end-users. With the support of a comprehensive set of experiments, the AntArmour mechanism proved that it is qualified to accurately identify the video and network characteristics that have a major impact on quality. Furthermore, by using these details in the decision-making process it provides both higher QoE and the efficient handling of the wireless channel resources.

The results of the experiments demonstrated that AntArmour outperformed all the adaptive and non-adaptive contestants in terms of the improvement of the video quality as well as in decreasing the network footprint. In the video quality issue on the urban environment, the proposed mechanisms had an SSIM improvement of more than 73% when compared to the baseline and more than 10% in comparison to its main competitor. The VQM scores experienced a reduction (which is desirable) of more than 39% compared to the main competitor and almost 77% against the baseline. The proposed mechanism also had a good performance in the highway environment. It achieved SSIM scores over 63% higher against the baseline and more than 11% against its main competitor. The VQM values followed the same pattern, showing a decrement of 41% and 74% in comparison to the main competitor and the baseline, respectively.

Another important feature of the proposed mechanism is to reduce the network footprint. The experiments showed an overhead decrement between 25 and 68% in the urban environment and a downsizing ranging from 28 to 72% in the highway scenario. The AntArmour mechanism improved the QoE of the transmitted videos without incurring in unnecessary network overhead. This allows enhancing the end-users perception and, at the same time, saving wireless network resources. As future work, a different set of mechanisms, mobility scenarios, and environments are going to be implemented and evaluated. In addition, other network-related parameters are going to be assessed as well as a testbed implementation using real equipment and vehicles.

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References

1. comScore: Brazilian online video audience reaches 43 million unique viewers in december 2012. Technical report, comScore inc. (February 2013). http://www.comscore.com/Insights/Press_Releases/2013/2/Brazilian_On-line_Video_Audience_Reaches_43_Million_Unique_Viewers_in_December_2012.
2. Adobe Digital Index: U.S. digital video benchmark report. Technical report, Adobe (Q2 2014).
3. Cisco: White paper: Cisco VNI forecast and methodology, 2015–2020. Technical report, Cisco (June 2016). http://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/complete-white-paper-c11-481360.html.
4. Cisco: White paper: Cisco VNI forecast and methodology, 2016-2021. Technical report, Cisco (September 2017). http://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/complete-white-paper-c11-481360.html
5. Zhou, L., Zhang, Y., Song, K., Jing, W., & Vasilakos, A. V. (2011). Distributed media services in p2p-based vehicular networks. *IEEE Transactions on Vehicular Technology*, *60*(2), 692–703.
6. Gerla, M., Wu, C., Pau, G., & Zhu, X. (2014). Content distribution in VANETs. *Vehicular Communications*, *1*(1), 3–12. https://doi.org/10.1016/j.vehcom.2013.11.001.
7. Immich, R., Cerqueira, E., & Curado, M. (2015). Shielding video streaming against packet losses over vanets. *Wireless Networks*, 1–15. https://doi.org/10.1007/s11276-015-1112-z.
8. Immich, R., Cerqueira, E., & Curado, M. (2016). Towards a qoe-driven mechanism for improved h.265 video delivery. In *2016 Mediterranean Ad Hoc Networking Workshop (Med-Hoc-Net)* (pp. 1–8). https://doi.org/10.1109/MedHocNet.2016.7528427.
9. Soldo, F., Casetti, C., Chiasserini, C., & Chaparro, P. A. (2011). Video streaming distribution in vanets. *IEEE Transactions on Parallel and Distributed Systems*, *22*(7), 1085–1091. https://doi.org/10.1109/TPDS.2010.173.
10. Jiang, T., Wang, H., & Vasilakos, A. V. (2012). Qoe-driven channel allocation schemes for multimedia transmission of priority-based secondary users over cognitive radio networks. *IEEE Journal on Selected Areas in Communications*, *30*(7), 1215–1224.
11. Bellalta, B., Belyaev, E., Jonsson, M., & Vinel, A. (2014). Performance evaluation of ieee 802.11p-enabled vehicular video surveillance system. *IEEE Communications Letters*, *18*(4), 708–711. https://doi.org/10.1109/LCOMM.2014.022514.140206.
12. Immich, R., Cerqueira, E., & Curado, M. (2015). Adaptive qoe-driven video transmission over vehicular ad-hoc networks. In *IEEE conference on computer communications workshops (INFOCOM WKSHPS)*.
13. Marwaha, S., Srinivasan, D., Tham, C. K., & Vasilakos, A. (2004). Evolutionary fuzzy multi-objective routing for wireless mobile ad hoc networks. In *CEC2004 Congress On Evolutionary Computation* (Vol. 2, pp. 1964–1971). IEEE.
14. Zeng, Y., Xiang, K., Li, D., & Vasilakos, A. V. (2013). Directional routing and scheduling for green vehicular delay tolerant networks. *Wireless Networks*, *19*(2), 161–173.

15. Pham, T. A. Q., Piamrat, K., & Viho, C. (2014). Qoe-aware routing for video streaming over vanets. In *IEEE 80th Vehicular Technology Conference (VTC Fall)* (pp. 1–5). https://doi.org/10.1109/VTCFall.2014.6966141.
16. Wu, H., & Ma, H. (2014). Opportunistic routing for live video streaming in vehicular ad hoc networks. In *IEEE 15th international symposium on a world of wireless, mobile and multimedia networks (WoWMoM)* (pp. 1–3). https://doi.org/10.1109/WoWMoM.2014.6919002.
17. Zhang, X. M., Zhang, Y., Yan, F., & Vasilakos, A. V. (2015). Interference-based topology control algorithm for delay-constrained mobile ad hoc networks. *IEEE Transactions on Mobile Computing*, *14*(4), 742–754.
18. Nafaa, A., Taleb, T., & Murphy, L. (2008). Forward error correction strategies for media streaming over wireless networks. *IEEE Communications Magazine*, *46*(1), 72–79. https://doi.org/10.1109/MCOM.2008.4427233.
19. Immich, R., Borges, P., Cerqueira, E., & Curado, M. (2015). Qoe-driven video delivery improvement using packet loss prediction. *International Journal of Parallel, Emergent and Distributed Systems*, *30*(6), 478–493.
20. Dorigo, M., Maniezzo, V., & Colorni, A. (1996). Ant system: Optimization by a colony of cooperating agents. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, *26*(1), 29–41.
21. Sullivan, G. J., Ohm, J.-R., Han, W.-J., & Wiegand, T. (2012). Overview of the high efficiency video coding (hevc) standard. *IEEE Transactions on Circuits and Systems for Video Technology*, *22*(12), 1649–1668.
22. Asefi, M., Mark, J. W., & Shen, X. (2012). A mobility-aware and quality-driven retransmission limit adaptation scheme for video streaming over vanets. *IEEE Transactions on Wireless Communications*, *11*(5), 1817–1827. https://doi.org/10.1109/TWC.2012.030812.111064.
23. Talari, A., Kumar, S., Rahnavard, N., Paluri, S., & Matyjas, J. (2013). Optimized cross-layer forward error correction coding for h.264 avc video transmission over wireless channels. *EURASIP Journal on Wireless Communications and Networking*, *2013*(1), 1–13.
24. Rezende, C., Almulla, M., & Boukerche, A. (2013). The use of erasure coding for video streaming unicast over vehicular ad hoc networks. In *IEEE 38th conference on local computer networks (LCN)* (pp. 715–718). https://doi.org/10.1109/LCN.2013.6761318.
25. Naeimipoor, F., & Boukerche, A. (2014). A hybrid video dissemination protocol for vanets. In *IEEE International conference on communications (ICC)* (pp. 112–117). https://doi.org/10.1109/ICC.2014.6883304
26. Huynh-Thu, Q., & Ghanbari, M. (2008). Scope of validity of PSNR in image/video quality assessment. *Electronics Letters*, *44*, 800–8011.
27. Vlavianos, A., Law, L. K., Broustis, I., Krishnamurthy, S. V., & Faloutsos, M. (2008). Assessing link quality in ieee 802.11 wireless networks: Which is the right metric? In IEEE 19th international symposium on personal, indoor and mobile radio communications, PIMRC 2008 (pp. 1–6). https://doi.org/10.1109/PIMRC.2008.4699837.
28. Wan, Z., Xiong, N., & Yang, L. (2015). Cross-layer video transmission over IEEE 802.11e multihop networks. *Multimedia Tools and Applications*, *74*(1), 5–23. https://doi.org/10.1007/s11042-013-1447-3.
29. Martini, M. G., Mazzotti, M., Lamy-Bergot, C., Huusko, J., & Amon, P. (2007). Content adaptive network aware joint optimization of wireless video transmission. *IEEE Communications Magazine*, *45*(1), 84–90. https://doi.org/10.1109/MCOM.2007.284542.
30. Immich, R., Cerqueira, E., & Curado, M. (2013). Cross-layer FEC-based mechanism for packet loss resilient video transmission. In Biersack, E., Callegari, C., Matijasevic, M. (Eds.) *Data Traffic Monitoring and Analysis. Lecture Notes in Computer Science* (Vol. 7754, pp. 320–336). Berlin: Springer. https://doi.org/10.1007/978-3-642-36784-7_13.
31. Immich, R., Cerqueira, E., & Curado, M. (2014). Towards the enhancement of uav video transmission with motion intensity awareness. In Wireless Days (WD), 2014 IFIP.
32. Dorigo, M., Birattari, M., & Stutzle, T. (2006). Ant colony optimization. *IEEE Computational Intelligence Magazine*, *1*(4), 28–39.
33. Gutjahr, W. J. (2000). A graph-based ant system and its convergence. *Future Generation Computer Systems*, *16*(8), 873–888. https://doi.org/10.1016/S0167-739X(00)00044-3.
34. Greengrass, J., Evans, J., & Begen, A. C. (2009). Not all packets are equal, part i: Streaming video coding and SLA requirements. *IEEE Internet Computing*, *13*, 70–75. https://doi.org/10.1109/MIC.2009.14.
35. Bentley, J. L., Preparata, F. P., & Faust, M. G. (1982). Approximation algorithms for convex hulls. *Communications of the ACM*, *25*(1), 64–68. https://doi.org/10.1145/358315.358392.
36. Henderson, T. R., Roy, S., Floyd, S., & Riley, G. F. (2006). Ns-3 project goals. In *Proceeding from the 2006 workshop on Ns-2: The IP network simulator*. WNS2 '06. ACM, New York, NY, USA. https://doi.org/10.1145/1190455.1190468.
37. Breslau, L., Estrin, D., Fall, K., Floyd, S., Heidemann, J., Helmy, A., et al. (2000). Advances in network simulation. *IEEE Computer*, *33*(5), 59–67.
38. Klaue, J., Rathke, B., & Wolisz, A. (2003). EVALVID—A framework for video transmission and quality evaluation. In International conference on modelling techniques and tools for computer performance evaluation (pp. 255–272).
39. Xiph.Org: Xiph.org Video Test Media (derf's collection). Retrieved February 18, 2016 from http://media.xiph.org/video/derf/
40. Staelens, N., Sedano, I., Barkowsky, M., Janowski, L., Brunnstrom, K., & Le Callet, P. (2011). Standardized toolchain and model development for video quality assessment—The mission of the joint effort group in VQEG. In *Quality of Multimedia Experience (QoMEX)* (pp. 61–66). https://doi.org/10.1109/QoMEX.2011.6065713.
41. ITU-T J.247: Objective Perceptual multimedia video quality measurement in the presence of a full reference. Recommendation J.247. *International Telecommunications Union*.
42. Eichler, S. (2007). Performance evaluation of the IEEE 802.11p wave communication standard. In IEEE 66th vehicular technology conference, VTC-2007 Fall. (pp. 2199–2203). IEEE
43. Jiang, D., & Delgrossi, L. (2008). IEEE 802.11p: Towards an international standard for wireless access in vehicular environments. In IEEE vehicular technology conference, VTC Spring 2008 (pp. 2036–2040). IEEE. https://doi.org/10.1109/VETECS.2008.458.
44. Katsaros, K., Dianati, M., Tafazolli, R., & Kernchen, R. (2011). CLWPR—A novel cross-layer optimized position based routing protocol for vanets. In IEEE vehicular networking conference (VNC) (pp. 139–146). https://doi.org/10.1109/VNC.2011.6117135
45. Behrisch, M., Bieker, L., Erdmann, J., & Krajzewicz, D. (2011). Sumo–simulation of urban mobility. In *The 3rd International Conference on Advances in System Simulation (SIMUL 2011)*. Barcelona, Spain.
46. Mittag, J., Papanastasiou, S., Hartenstein, H., & Strom, E. G. (2011). Enabling accurate cross-layer PHY/MAC/NET simulation studies of vehicular communication networks. *Proceedings*

of the IEEE, 99(7), 1311–1326. https://doi.org/10.1109/JPROC.2010.2103291.

47. Taliwal, V., Jiang, D., Mangold, H., Chen, C., & Sengupta, R. (2004). Empirical determination of channel characteristics for dsrc vehicle-to-vehicle communication. In *Proceedings of the 1st ACM international workshop on vehicular ad hoc networks, VANET '04* (pp. 88–88). New York, NY: ACM. https://doi.org/10.1145/1023875.1023890.
48. Winkler, S., & Mohandas, P. (2008). The evolution of video quality measurement: From PSNR to hybrid metrics. *IEEE Transactions on Broadcasting*, *54*(3), 660–668. https://doi.org/10.1109/TBC.2008.2000733. IEEE Broadcast Technology Society.
49. Pinson, M. H., & Wolf, S. (2004). A new standardized method for objectively measuring video quality. *IEEE Transactions on broadcasting*, *50*(3), 312–322.
50. Wang, Z., Bovik, A. C., Sheikh, H. R., & Simoncelli, E. P. (2004). Image quality assessment: From error visibility to structural similarity. *IEEE Transactions on Image Processing*, *13*(4), 600–612. https://doi.org/10.1109/TIP.2003.819861.
51. Chikkerur, S., Sundaram, V., Reisslein, M., & Karam, L. J. (2011). Objective video quality assessment methods: A classification, review, and performance comparison. *IEEE Transactions on Broadcasting*, *57*(2), 165–182. https://doi.org/10.1109/TBC.2011.2104671.
52. Vatolin, D., Moskin, A., Pretov, O., Trunichkin, N. *MSU video quality measurement tool*. Retrieved February 18, 2016 from http://compression.ru/video/quality_measure/video_measurement_tool_en.html

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