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QoE-driven video delivery improvement using packet loss prediction

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The video delivery over wireless networks has risen in popularity in the recent years. However, in order to provide a high quality of experience (QoE) to the end users, it is necessary to deal with several challenges ranging from the fluctuating bandwidth and scarce resources to the high error rates. The use of these error-prone networks unveils the need for an adaptive mechanism to ensure the quality of the delivered video streams. Adaptive forward error correction (FEC) techniques with QoE assurance are desired to protect the stream, preserving the video quality. The adaptive FEC-based mechanism proposed in this article uses several video characteristics and packet loss rate prediction to shield real-time video transmission over static wireless mesh networks, improving both user experience and the usage of resources. This is possible through a combination of a random neural network, to categorise motion intensity of the videos, and an ant colony optimisation scheme, for dynamic redundancy allocation. The benefits and drawbacks are demonstrated through simulations and assessed with QoE metrics, showing that the proposed mechanism outperforms both adaptive and non-adaptive schemes.

Keywords: forward error correction (FEC); video-aware FEC; motion vectors (MVs); QoE; neural networks; ant colony optimization; unequal error protection (UEP); packet loss rate prediction

1. Introduction

The usage of online video services has been increasing rapidly in recent years, particularly from wireless mobile devices [8]. This upswing is related to several technological improvements in mobile devices, as well as the rise in popularity of this type of content. Several companies have used live video services to reduce costs and increase both collaboration and productivity. Following the same trend, the number of non-professional users creating, sharing and consuming online videos is growing apace. Because of the video traffic ascendance, the probability of errors arising from interference and network congestion increases. This unveils the need for an adaptive mechanism to shield the video delivery, otherwise, the above factors will impact on the video quality, degrading the quality of experience (QoE) for the end users.

The QoE can be described as the overall acceptability of end users which is related to, but differs, from the broadly studied concept of quality of service (QoS). In other words, the QoE metrics assess the video quality considering the end users point-of-view, thus, it has to be contemplated in the adaptive mechanisms. An efficient QoE-aware video transmission mechanism is one of the main challenges in wireless networks. For this reason, it is crucial to specify a precise adaptive scheme that uses QoE, video

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characteristics and the network's state to make an efficient use of the available resources, while improving the video quality for end users [13].

Video sequences have unique characteristics that can be explored to improve the transmission quality. One of them is the motion intensity (MI) [16]. For example, a video with high motion activity or panning and zooming scenes will have high MI. On the other hand, a sequence with a steady camera with low motion activity will have low MI. In the case of losses in a high MI frame, the QoE will be more affected than when having the same loss on a low MI frame. Under the conditions given, video sequences with greater MI will need more protection than those with a lower one. The same situation is evidenced according to the network state. Networks with a greater packet loss rate (PLR) need better protection than those with a lower one. Thus, in order to improve the video quality, protection mechanisms are necessary to adapt to both the video's characteristics and the network's state.

Forward error correction (FEC) techniques have been used successfully to protect the transmission of real-time video services [22]. This technique provides a robust video transmission through redundant information that is sent along with the original data-set. This means that if some information is lost, it is possible to rebuild the original set using the redundant information. While this is true, non-adaptive FEC mechanisms that use a fixed amount of redundancy tend to demonstrate a greedy behaviour towards the network resources. This can lead to an aggravation of network traffic congestion as a result of an undisciplined use of redundancy.

Adaptive FEC mechanisms can be used to surpass the aforementioned limitations. In this case, an unequal error protection (UEP) scheme can be used to allocate different amounts of redundant information to different units of data. This allows the protection of the most important information according to the human perception, resulting in better QoE [11]. Because of this, an adaptable FEC-based mechanism that combines UEP and QoE is required to downsize the redundancy amount, while increasing the human perception of the quality of the video.

Several techniques can be adopted to enable the use of UEP, such as random neural networks (RNN) [1] and ant colony optimisation (ACO) [9]. RNNs are a type of neural networks that provide an information-processing paradigm based on the central nervous system. Through a learning process, based on pattern reading and connection weight adjustment, it is possible to configure these techniques for a specific application, being widely used in pattern recognition and data classification [2,21]. The ACO is a probabilistic algorithm, based on the behaviour of ants, used to dynamically solve computational problems by finding the best path in a graph. In this solution, ants span through the paths between the nodes to find a solution. In every path followed, a pheromone marker is deposited. At the end, the paths with greater amount of pheromone represent best-fitted solutions [12].

The information used as input for the UEP enabler techniques ranges from video characteristics to the network details. The video-related information is the frame size and type, the number of motion vectors (MVs), as well as the Euclidean distance described by the MV. The adoption of the MV information plays an important role on the adaptation mechanism, because through it, it is possible to characterise the MI of the video sequences that are being transmitted. As already mentioned, the MI is important to understand how resilient to losses is a specific video sequence [14].

Besides the video characteristics, the network details, particularly the PLR, are also noteworthy in order to maintain a good video quality. The PLR is, in general, a good indicator of the connection quality. However, the simple use of past PLR values does not always properly characterise the future PLR [26]. Taking this into consideration, a PLR prediction mechanism is required. Forecasting future events in real time is a very difficult task. There are several proposals using time-series [5], sparse basis model [3] and hidden Markov model (HMM) [27]. However, they are either unable to operate in real time or depend on heavy static off-line training.

In the light of the aforementioned traits, this article proposes a novel adaptive UEP- and QoE-aware mechanism based on RNN, ACO and packet loss prediction (PredictiveAnts). The main goal is to ensure a high QoE for the end user while downsizing the network overhead. The PredictiveAnts mechanism will categorise the importance of the video data that are being transmitted, over static wireless mesh networks, allowing the protection of the most important information.

The remainder of this article is structured as follows. The related work is presented in Section 2. Section 3 describes the PredictiveAnts and its evaluation is presented in Section 4. Conclusions and future work are summarised in Section 5.

2. Related work

Several techniques have been proposed to enhance the quality of video transmissions over wireless networks. The adaptive hybrid error correction model (AHECM) solution adopts a dynamic FEC block length [30]. This FEC block can be adjusted in real time depending on Markov models to estimate the PLR and the number of continuous losses, to boost video transmissions. This mechanism is heavily based on network parameters leaving out important QoE-sensitive information such as frame size and type as well as the MI. Furthermore, the mechanism uses a buffer to cope with the impact of packet disordering. This should increase delay and lead to the discarding of the packets by the encoder due to playback time out.

The cross-layer mapping unequal error protection (CLM-UEP) [20] is a technique that adds a specific amount of redundant information using a Reed–Solomon (RS) erasure code. The amount of redundancy is defined through the analysis of the frame type and the past PLR. The mechanism was assessed using the playable frame ratio (PFR) and peak signal-to-noise ratio (PSNR). Nonetheless, the past PLR may not repeat in the near future leading to a mischaracterisation of the network. Moreover, the average PLR will not capture fast time-varying changes in the wireless network channels. In addition, the CLM-UEP does not take into consideration the video MI, which has a significant weight on the determination of a precise amount of redundancy.

Another mechanism is the optimised cross-layer FEC (OCLFEC) [28], which computes priority values based on the mean squared error of each frame. Two error correction codes are used, namely Luby transform (LT) and rate-compatible parity check (RCPC). The former is used to encode the data and the latter to add check bits. Performance optimisations are made on both for specific situations. The mechanism is assessed in terms of QoS performance, which does not guarantee a good QoE for end users. Besides that, the OCLFEC does not take into account the MI and the network state, leaving out important characteristics that should be considered to protect video sequences.

An additional work proposes the use of a two-state Markov hierarchical model to predict the short-term losses and HMMs to forecast the longer-term network losses [27]. In doing this, both the PLR and burstiness are categorised and used as input to configure the amount of redundancy added by the FEC scheme. The assessment is performed with the perceptual evaluation of speech quality (PESQ) and mean opinion score (MOS) metrics. This proposal does not consider the video characteristics in the decision-making process. These characteristics are known to have a direct impact on the video resiliency to packet loss and consequently on the QoE for the end users.

The ‘Transport Audiovisuel avec Protection Ingale des Objets et Contrle d’Admission’ (TAPIOCA) mechanism divides each group of pictures (GoPs) by layers assigning different priority values to each one [19]. This allows the protection of the most important layers. The assessments of the mechanism were performed by the decodable frame rate (DFR) and the protection system efficiency (PSE) metrics. The division of GoPs into layers requires high processing power, making it not suitable for real-time services. In addition, the mechanism does not take into consideration the MI of the video sequences, which can have a considerable influence on the perceived impairments.

Another mechanism is the adaptive packet and block length FEC (APB-FEC) [29]. This mechanism uses smaller packet lengths in order to increase the size of the FEC block. A feedback channel is used to receive packet loss information in order to adapt the video sequences to the network characteristics. As aforementioned, the use of past PLR can lead to an inaccurate characterisation of the network due to outdated information. The performance assessment is based on the effective PLR, the network overhead and PSNR metric. However, the PSNR metric is known to not correlate well with how the QoE is perceived by end users.

The video aware FEC-based (ViewFEC) mechanism has a modular design and performs the analysis of the MI characteristics [14]. Through a MI database, which is created offline using several video sequences, a heuristic comparison is carried out between it and the live video stream. This comparison produces the MI of the video that is being transmitted. A complete QoE assessment is performed using both objective metrics, such as the structural similarity (SSIM) and the video quality metric (VQM), and subjective metrics, such as MOS. Nevertheless, this mechanism heavily relies on the offline database which may not provide optimal results. In addition, it does not use any type of packet loss information in the adaptation process, which can lead to unnecessary network overhead.

Table 1 provides an overview of the aforementioned adaptive FEC-based mechanisms according to some of their characteristics, such as the metrics used to assess the performance, use of the MI and the manner in which packet losses are employed. As evidenced, all the works fail in producing a complete mechanism to provide resilient video transmission without imposing unnecessary network overhead. Only the PredictiveAnts mechanism contemplates all the aforementioned limitations and improves on them to conceive a novel FEC-based QoE-driven adaptive scheme to shield video delivery over wireless networks.

Table 1. Related work mechanisms.

Mechanism	Erasure code	Metrics	MI-aware	Loss information
AHECM	RS	DFR, PSNR	No	Predictive
CLM-UEP	RS	PFR, PSNR	No	Past PLR
OCLFEC	LT, RCPC	PSNR	No	None
HMM	RS	PESQ, MOS	No	Predictive
Tapioca	RS	DFR, PSE	No	None
APB-FEC	RS	Overhead, effective PLR, PSNR	No	Past PLR
ViewFEC	RS	Overhead, SSIM, VQM, MOS	Yes	None
PredictiveAnts	RS	Overhead, SSIM, VQM	Yes	Predictive

3. QoE-driven motion- and video-aware mechanism

Considering the open issues aforementioned, particularly the absence of QoE and motion-aware mechanisms that use a broad amount of video characteristics together with PLR prediction, this work presents a novel QoE-driven motion- and video-aware mechanism (PredictiveAnts). The main goal is to strengthen the transmission of online videos in dynamic wireless networks with the aid of a packet loss prediction mechanism. The PredictiveAnts is an enhancement of our previous work [12] and the main improvements are described in next sections.

3.1 PredictiveAnts overview

Figure 1 depicts the PredictiveAnts mechanism. It is composed of two processes, one is performed offline and the other one in real time. The offline process is responsible for the RNN training and validation steps. The main objective of the RNN is to characterise the MI of video sequences according to several inputs, such as the frame type and size, the number of MVs, and the Euclidean distance pointed by these vectors. Since it is an offline process, it needs to be executed only once. After that, the RNN can be used in real time. The offline process is important because it allows a fast and more accurate real-time execution, since few variables need to be handled.

The real-time process consists of several modules, each one having very peculiar tasks, as follows:

- Motion intensity – The MI characterisation is performed by the RNN in real time since it was already trained and validated in the offline process.
- Feedback receiver – The feedback mechanism is responsible for the retrieval of loss statistics. The information is collected by the receiver and sent to the transmitter.
- Loss rate prediction – Using the feedback statistics, the properties of the error probability are estimated on the server side.

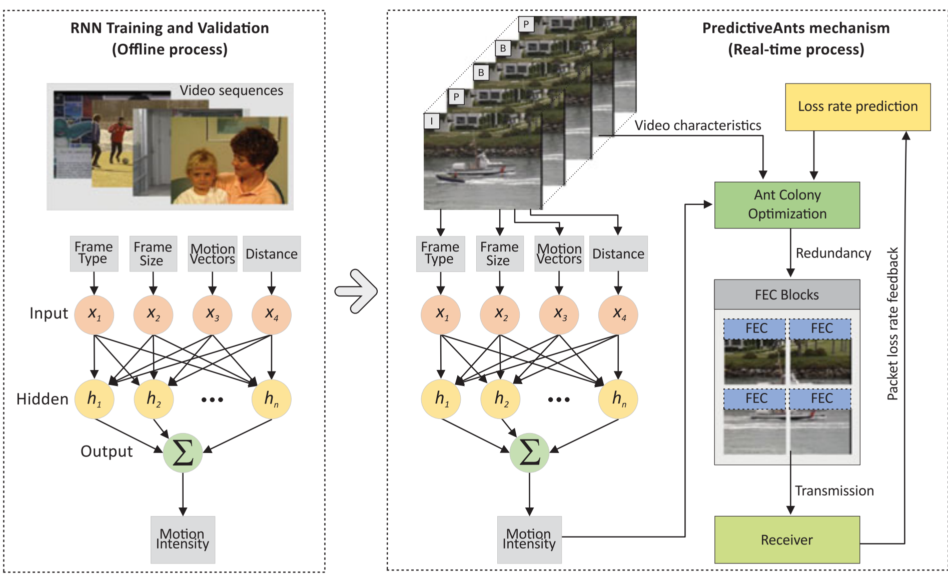

Figure 1. PredictiveAnts mechanism.

- Video characteristics – This module fetches information from the video sequences that are being transmitted to identify video characteristics such as the frame type and size, as well as the MVs.
- Ant colony optimisation – The ACO is responsible for making a joint analysis of all the information gathered by the other modules, establishing the most suitable amount of redundancy to each FEC block.
- FEC blocks – The FEC blocks are built and a specific amount of redundancy designed by the ACO is assigned to each one.

3.2 Into the design of PredictiveAnts

As previously mentioned, the PredictiveAnts comprises several process and modules that are going to be detailed in this section. First of all, in the same way as in the previous mechanism, it is necessary to train and validate the RNN for MI categorisation. Further details can be found in [12]. The RNN is composed of four input nodes, seven hidden nodes and one output node. The input nodes are the frame size, the frame type, the number of MVs and the Euclidean distance described by the vectors. The hidden nodes are generated through a stochastic process whereas the output node gives the MI value. The RNN was trained using a set that comprises distinct motion scenarios, and validated with another different set. The selection of the sets was performed through an exploratory hierarchical cluster analysis to group several video sequences according to the MI. Several video characteristics are used in this analysis, such as frame type, frame size and MVs. The results are well-defined clusters that can be used in the RNN. As aforementioned, the offline process needs to be executed only once and after that, the RNN can be used in real time.

After the offline process all further computations are done in real time. One of the main improvements of our novel solution is the design and use of a simple error prediction scheme. This is performed, instead of just using the instantaneous network loss rate, to attribute a customised amount of redundancy to the video sequence being transmitted. The use of a loss prediction scheme enables a further reduction of added overhead, by balancing the allocation of redundancy data between the network's good and bad states.

Forecasting future events is a very important task, as the predicted data can be used as input for the decision-making process. As aforementioned, there are several proposals to forecast the PLR using, for example, time-series, sparse basis models and HMMs. However, as we need a fast mechanism, which should be able to run in real time, a simpler model was designed. Thereby, the error prediction scheme was developed based on the concept of good and bad gaps [15]. In order to do that, a feedback mechanism was implemented to enable the retrieval of loss statistics. This feedback information comprises the distribution of good and bad gaps during transmission. As shown in Figure 2, a good gap is considered as the interval of packets that were successfully received between two

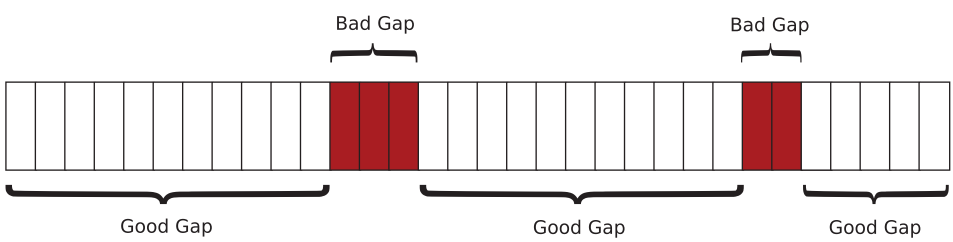

Figure 2. Packet gaps during transmission.

bad gaps (white squares). A bad gap is the interval of packets during which a burst of errors is occurring (red squares). The feedback information is collected by the receiver and sent to the transmitter in the form of a vector containing the size of every gap of each type. From the measured statistics, the characteristics of the error probability can be computed on the server side. This information is used as a predicting value of a higher probability for the occurrence of an error in the next block of packets to be transmitted. Therefore, the error prediction scheme has an influence on ACO, leading to an adjustment in redundancy based on the prediction of the occurrence/non-occurrence of an error.

Another enhancement in PredictiveAnts is the use of FEC blocks. This means that, instead of performing redundancy allocation on a frame-by-frame basis, the mechanism was improved to support the transmission of each frame on blocks of several packets. The size of the blocks can be adjusted according to video and/or network characteristics. In our case, the size of the blocks was set to 10 network packets. This value was selected through extensive experimentation to provide more flexibility of the mechanism, while dealing with the error correcting code, and better control over the data. Furthermore, this provides enough granularity to comply with the sizes of the gaps. Therefore, the selected packet block size was that which allowed for the block to be isolated (i.e. whole block inside a good gap) from an error gap through error prediction in all PLR conditions.

Once the information about the MI, video characteristics and the packet loss prediction is gathered, the ACO mechanism begins to operate. Through the aforementioned information, the exact amount of redundancy needed for each FEC block is computed in real time. In doing that, it is possible to minimise the wireless network overhead while maximising the QoE.

Figure 3 shows PredictiveAnts ACO graph. It has 14 nodes characterising video and network details. These nodes were chosen because they represent a combination of factors that directly affect the video quality, as follows:

- Start – The first node is just the starting point. As the total amount of redundancy is given by the travelled path all ants must start at the same point.

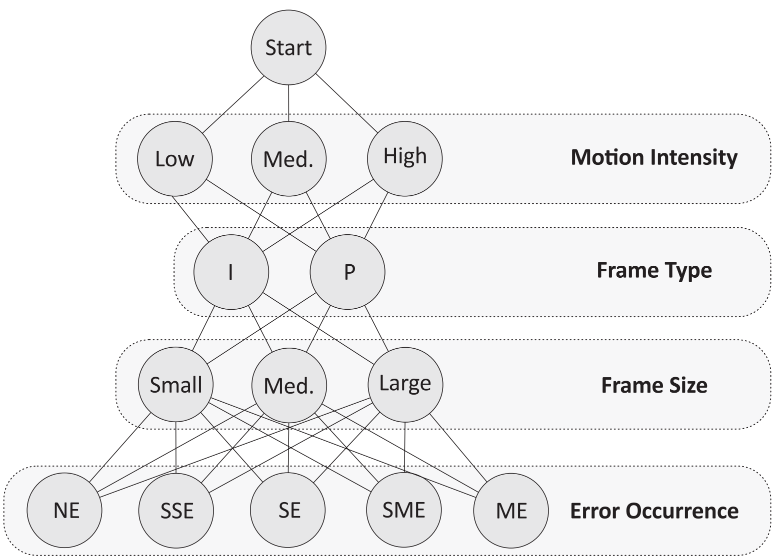

Figure 3. Graph used in the ACO mechanism.

- Motion intensity – These three nodes feature the RNN classification in terms of MI, which can be low, medium and high motion.
- Frame type – The frame type, I- or P-frame, is represented by these two nodes. These are the most important frames in the MPEG standard. The loss of one I- or P-frame will be more noticeable by the end user because the error will only be corrected when another I-frame arrives, in other words, in the beginning of the next GoP. Thus, those frames need to be protected with redundant information.
- Frame size – These three nodes characterise the frame size, which can be small, medium and large.
- Error occurrence – The last layer of nodes represents the possibility of occurrence of an error instead of the instantaneous PLR. The five nodes represent five different scenarios which can occur:
  - NE (no error) – It is a scenario where no error is accounted for the current FEC block.
  - SSE (Shared single error) – In this scenario, a single error is predicted, which will be shared by this FEC block and the next.
  - SE (Single error) – A single error is predicted only for the current FEC block.
  - SME (Shared multiple errors) – It is a scenario where the occurrence of two or more error gaps is predicted in the current FEC block continuing to the next one.
  - ME (Multiple errors) – In this scenario, two or more blocks of errors occur only on the current FEC block.

A simple ACO model was used with both the number of iterations and ants set to 10. The values were reached through extensive experimentation to obtain a solution which did not worsen the delay of the PredictiveAnts mechanism. In run time, the ants search the graph while leaving pheromone in the travelled path, this reinforces the best solutions for the problem which can be re-used for similar conditions. The value computed by the ACO mechanism will be used to configure the amount of redundancy in the RS algorithm [24]. This algorithm is of low complexity being suitable for real-time use. By adding a tailored amount of redundancy to each FEC block, it is possible to better protect the most QoE-sensitive data, maximising the video quality and, at the same time, minimising the network overhead.

Algorithm 1 shows the PredictiveAnts mechanism pseudo-code. All operations are repeated for each frame (01). The first step is to get the frame type (02). Since only I- and P-frames are protected, it is necessary to check this condition (03). If false, the frame is sent immediately (13). If true, other information about the frame is required, such as frame size (04), number of MVs (05) and the Euclidean distance of the MVs (06). All these are input information to the RNN for MI categorisation (07). Once the MI value is found, it can be fed to the ACO mechanism (08), together with the frame type, frame size and the loss rate prediction, to compute the amount of redundancy (09). Afterwards, the FEC blocks are built using the original frame and the redundancy (10) and then the blocks are sent (11). The feedback information about the packet loss is received (15) and the loss rate prediction is calculated (16).

3.3 Computational complexity of PredictiveAnts

The computational complexity of PredictiveAnts components is as follows. Equation 1 represents the ACO complexity of finding a solution with an expected number of in a

Algorithm 1: PredictiveAnts pseudo-code

```
for each Frame do
  FT ← getFrameType(Frame);
  if (FT equal (I- or P-Frame)) then
    FS ← getFrameSize(Frame);
    MV ← getMotionVectors(Frame);
    MVDist ← computeDistance(MV);
    MotionIntensity ← RNN(FT, FS, MV, MVDist);
    RSpar ← ACO(MotionIntensity, FT, FS, LP);
    Redundancy ← RS(RSpar);
    buildFECBlocks(Frame + Redundancy);
    sendFECBlocks(FB1, FB2, ..., FBn);
  else
    sendFrame(Frame);
  end
  LOSS ← receiverFeedback();
  LP ← calculateLossRatePrediction(LOSS);
end
```

graph with n nodes, m edges and where ρ is the evaporation rate of the pheromone used by the ants [4].

$$O\left(\frac{1}{\rho}n^2 \ m \ \log \ n\right). \tag{1}$$

Concerning RS, the encoding computational complexity comprises two steps, namely the pre-computing of the generator matrix (GM) of the code, followed by the multiplication of the source vector by the GM. Equation (2) represents the total computational complexity of the encoding per element [18], where k represents the rows and n represents the columns of the GM matrix.

$$O\left(\frac{k}{(n-k)} * (\log \ k)^2 + \log \ k\right). \tag{2}$$

The decoding steps of the RS code involve the computation of the k*k sub-matrix of the GM. Afterwards, this matrix is inverted and multiplied by the received vector in order to recover the original vector. The computational complexity [18] per element of these steps is represented by Equation (3) where k is the number of received elements.

$$O((\log \ k)^2) \tag{3}$$

Overall, the PredictiveAnts mechanism has the capability to be used in real time. Moreover, due to the accurate categorisation of the MI in the video sequences and the PLR prediction, the adaptive PredictiveAnts mechanism can downsize the network overhead, reducing the video delivery footprint, while improving the video quality.

4. Performance evaluation and results

The PredictiveAnts mechanism aims to improve the usage of wireless network resources by reducing the network overhead while assuring a good perceived video quality. The performance evaluation goal is to show that the PredictiveAnts mechanism can effectively decrease the network overhead while still providing high QoE. The evaluation experiments were carried out by using the Network Simulator 3 (NS-3) [25]. The scenario is composed of a grid of 25 static nodes (5 × 5), 90 m apart from each other. The optimised link state routing protocol (OLSR) [7] was used as the routing protocol. A dataset of 10 video sequences with common intermediate format (CIF), GoP length of 19:2 and H.264 codec were used. The selected video sequences are different from those used to train the RNN. These videos cover different distortions and subjects, which represent content usually found in on-line video services. Furthermore, the selected video sequences include still and cut scenes, colour and luminance stress as well as distinct motion energy and spatial detail. The frame-copy error concealment method was used, which means that the lost frames are replaced by the last good one received. Table 2 shows the simulation parameters.

In order to simulate the burst loss patterns found in wireless networks [32], a simplified two-state discrete-time Markov chain scheme following the Gilbert-Elliot (GE) packet-loss model [23,33] was implemented. The GE model is widely used and accepted by the scientific community as a good fit for describing the error patterns burstiness in wireless channels. There are studies that show that this model is appropriate to describe the observed loss pattern in real-life network traces [10]. In addition, the use of an error model provides a much higher level of abstraction. Through them, it is possible to assess the impact of different burstiness error patterns as well as distinct error rates. The GE model comprises two nodes representing a good (G) and bad (B) state. In the simplified model at the G state no packets are lost, on the other hand, at the B state all packets are lost. The transitioning probability between the two states is what defines the amount of packet loss. By adjusting these probabilities it is possible to generate different error patterns, which can be translated to specific PLR values. In our case these values were set to 5%, 10%, 15% and 20%, which are commonly present in wireless networks.

Five different cases were simulated as follows: (1) without any type of FEC. This case will serve as baseline to compare with the others; (2) video-aware equal error protection (VaEEP) (where both I- and P-frames are equally protected) with a pre-defined amount of redundancy is set to 38%; (3) video-aware UEP (VaUEP), here again both I- and P-frames are protected, this time, however, with a different amount of redundancy depending on the type. An average of 30% redundancy amount is added. It is important to notice that the protection of only I- and P-frames is a common practice in the video transmission industry. The redundancy amounts used by both VaEEP and VaUEP mechanisms were attained

Table 2. Simulation parameters.

Parameters	Value
Display size	CIF – (352 × 288)
Frame rate mode	Constant
Frame rate	29.970 fps
GoP	19:2
Codec	H.264
Container	MP4
Error concealment method	Frame-copy
Wireless standard	IEEE 802.11 g
Propagation model	FriisPropagationLossModel
Routing protocol	OLSR
Number of nodes	25 nodes (grid of 5 × 5)
Error model	Simplified Gilbert-Elliot

after a thorough set of simulation studies. They showed, on average, a good tradeoff between video quality and network overhead under the different PLR; the next case is our previous mechanism (AntMind) which uses a combination of an RNN and ACO for UEP [12]; finally, the last case adopts our novel PredictiveAnts mechanism.

Two main QoE metrics were employed to carry out the video quality assessment, namely SSIM and VQM. Both metrics are among some of the most widely used to this end [6]. The SSIM analyses the structural similarity, contrast and luminance of the transmitted images to rank it according to the likeness from the original data. Values closer to one represent better video quality. VQM uses a discrete cosine transform to assess the spatial–temporal property of the human visual system, allowing it to evaluate the image distortion. Values closer to zero represent better video quality. The objective quality assessment was conducted using Evalvid [17] and MSU Video Quality Measurement Tool (VQMT) [31].

Figure 4 shows the network overhead results of all PLRs using the four FEC schemes. The first scheme, without FEC, is not shown because it does not produce overhead. VaEEP's average overhead was 38% with values ranging from 35% to 43%, and VaUEP's average overhead was 30% with values ranging from 25% to 36%. Our previous mechanism (AntMind) had an average overhead of 15%, with values between 9% and 19%. This is a notable result, with an overall reduction of more than 50% in the redundancy amount (60% over VaEEP and 50% over VaUEP). The novel PredictiveAnts was able to produce even better results, providing an average overhead of 11%, with values ranging from 7% to 13%. This represents a further improvement of on average over 27% less redundancy. This means that far less redundancy data are used by the PredictiveAnts opposed to VaEEP, VaUEP and AntMind.

In addition, it is worth pointing out that PredictiveAnts correctly characterises the importance of the frames according to their MI details. This allows adding less redundant information to sequences with a lower MI and also adding more redundancy to higher MI video sequences. In all video sequences PredictiveAnts outperforms the previous AntMind mechanism. However, the biggest reductions in the network overhead were achieved on

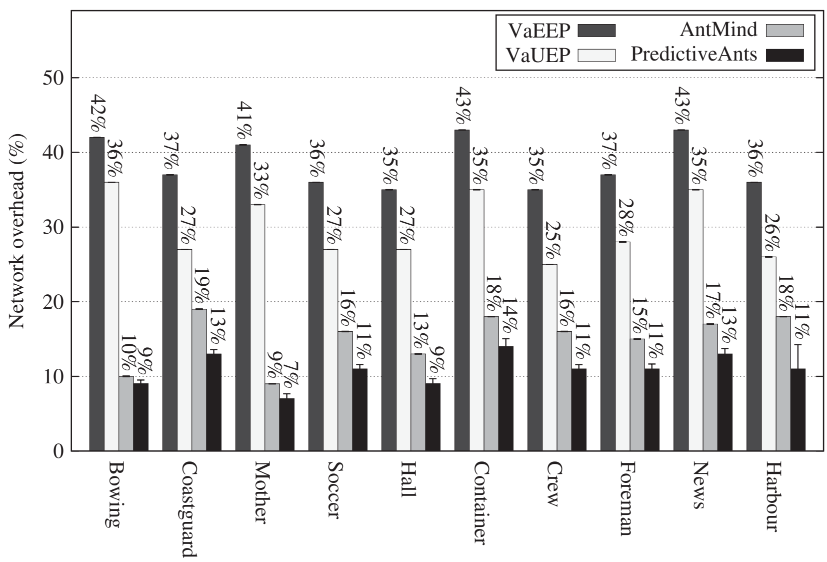

Figure 4. Network overhead.

the video sequences which have greater amounts of MI, such as Harbour (36%) and Coastguard (33%). The lowest reductions in the network overhead were found on the videos that are opposite to these two in terms of MI, specifically Bowing (11%) and Mother (17%). Since the PredictiveAnts mechanism is an enhancement of AntMind, the greater gain in the overhead reduction has already been achieved. Therefore, this explains why the video sequences with lower intensities of motion had a slight reduction in the network overhead.

An objective assessment of the transmitted videos was performed using SSIM and VQM metrics to ensure that the video quality was preserved. Figure 5 shows the SSIM assessment for all of the video sequences in each of the five schemes. The values are an average of all PLRs for each video. The scheme without FEC averaged a value of 0.806. The VaEEP mechanism averaged a value of 0.880 and the VaUEP obtained 0.881. The AntMind mechanism had an average of 0.876 and the PredictiveAnts score 0.884, which was the highest average value. The distinct values for the different video sequences are due to the unique characteristics of each video, this highlights the need for a motion- and video-aware mechanism. These results therefore show that the PredictiveAnts mechanism offers a better video quality than the previous AntMind mechanism. Taking this into account and the reduction of the added overhead, we can say that it provides an even more precisely tailored protection scheme.

Figure 6 presents the VQM scores. The scheme without FEC averaged a value of 5.277. The VaEEP and VaUEP mechanisms had an average of 3.895 and 3.860, respectively. The AntMind mechanism achieved an average of 3.940 and the PredictiveAnts scores 3.664. The same way as in the SSIM assessment, the PredictiveAnts had the better video quality. This proves once again that the improvements made to the PredictiveAnts were able to reduce the network overhead while improving the video quality.

Table 3 summarises the SSIM, VQM and network overhead results. It demonstrates that the proposed mechanism was able to considerably cut down the network overhead by

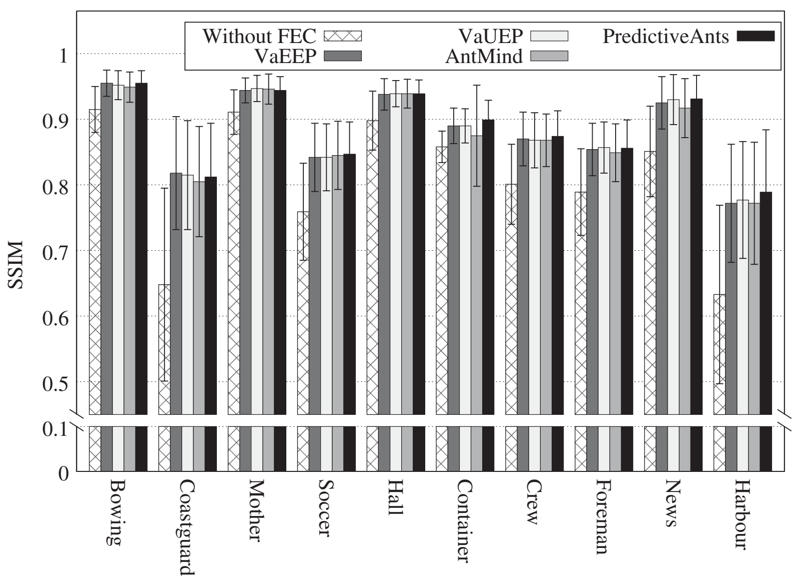

Figure 5. Objective QoE assessment (SSIM).

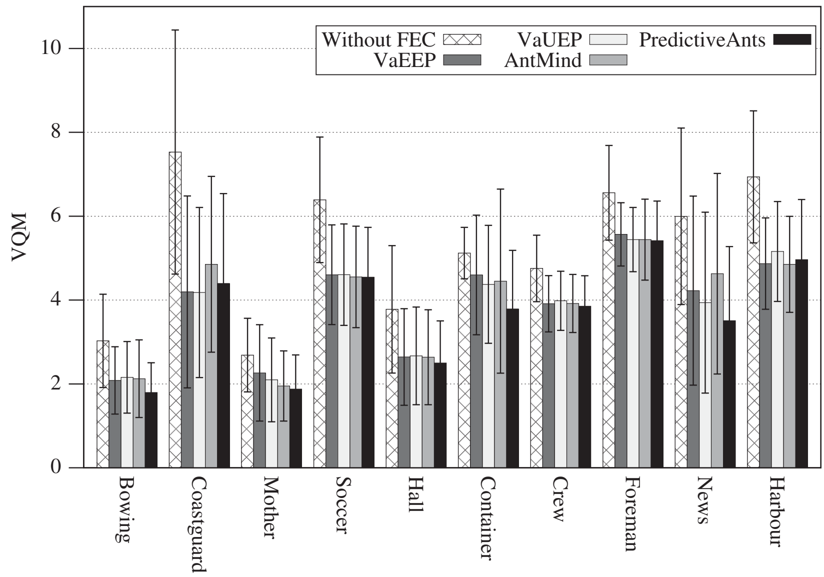

Figure 6. Objective QoE assessment (VQM).

Table 3. Average SSIM, VQM and network overhead.

	PredictiveAnts	AntMind	VaEEP	VaUEP	Without FEC
SSIM	0.884	0.876	0.881	0.880	0.806
VQM	3.664	3.940	3.895	3.860	5.277
Overhead	10.970%	14.898%	38.460%	29.827%	–

not adding unnecessary redundancy. The PredictiveAnts achieved an average of 67% of redundancy reduction over the non-adaptive schemes (71% less redundancy than VaEEP and 63% less than VaUEP). It also provides a very good result over our previous AntMind mechanism, saving more than 27% in the network overhead. In addition, the PredictiveAnts mechanism managed to achieve the best results in terms of video quality. These outcomes are very important in wireless networks environments due to the already scarce network resources.

On the basis of the results referred to above, the PredictiveAnts mechanism showed that it can considerably reduce the network overhead. This is only possible due to an accurate categorisation of the MI details. In addition, the packet loss prediction scheme allows anticipating the amount of redundancy that will be needed before the transmission. In doing that, it shields the video delivery against losses by ensuring an adequate protection to any kind of video sequence. This leads to an improved QoE for end users.

5. Conclusion and future works

The ever-growing interest in online video streaming over wireless networks highlights the need for an adaptive QoE motion- and video-aware mechanism to shield the transmissions against packet loss. To fill this gap, the PredictiveAnts mechanism proposed and implemented a dynamic protection scheme of the most QoE-sensitive data. It allows an efficient use of resources and at the same time maximises the video quality. Both advantages and footprint of the PredictiveAnts mechanism were demonstrated through a set of experiments using a diverse assortment of real video sequences.

The experiment results evidenced that PredictiveAnts was able to enhance the video quality without adding an unnecessary amount of redundancy. In comparison to the non-adaptive mechanism, it has reduced the network overhead by 67% on average. When compared to the adaptive mechanism, it provides a further 27% savings in the network overhead. This is a great enhancement over both non-adaptive and adaptive FEC mechanisms. It reinforces the relevance of using adaptive FEC mechanisms, which take into consideration the MI and packet loss prediction to protect a video streaming with fluctuating characteristics. Future work should improve the loss prediction scheme by adding different methods to compute it. In addition, other adaptive FEC mechanisms will be used to assess the effectiveness of PredictiveAnts. Different scenarios will be explored, especially using mobility and cross-traffic situations to determine the resilience of the proposed mechanism under such conditions.

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No potential conflict of interest was reported by the authors.

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