AntMind: Enhancing Error Protection for Video Streaming in Wireless Networks

Roger Immich[1], Pedro Borges
University of Coimbra
Coimbra, Portugal
immich@dei.uc.pt,
pborges@student.dei.uc.pt

Eduardo Cerqueira[1]
Federal University of Para - Belem, Brazil
University of California Los Angeles (UCLA)
Los Angeles, USA
cerqueira@upfa.br

Marilia Curado
University of Coimbra
Coimbra, Portugal
marilia@dei.uc.pt

***Abstract*—On-line video services are becoming a large part of the daily routines of people all over the world, where most of the content is accessed through wireless networks. Therefore, it is of ever growing importance that the negative aspects of these types of error prone networks are lessened in order to ensure adequate quality of the delivered video streams. Forward Error Correction (FEC) techniques allow the stream to be protected with an amount of redundancy to preserve the video quality during transmission. Nevertheless, some FEC schemes do not make an efficient usage of the available network resources due to unnecessary use of redundancy as a result of video-unawareness. The adaptive FEC mechanism proposed in this paper uses the motion intensity characteristics of the video and the network loss state to deliver the video streaming with adequate Quality of Experience (QoE), while keeping the use of network resources to a minimum level. It does so from a combined use of a Random Neural Network (RNN) for motion intensity classification and an Ant Colony Optimization (ACO) scheme for dynamic redundancy allocation. QoE metrics are used to assess the performance of the mechanism showing its advantages over adaptive and non-adaptive protection schemes.**

***Index Terms*—Motion Vectors (MV); Forward Error Correction (FEC); Video-aware FEC; QoE; Neural networks; Unequal Error Protection (UEP); Ant Colony Optimization**

I. Introduction

The usage of real-time video services on the go has grown in recent years [1]. This leap can be explained by the technological advances in mobile devices and the increasing popularity of content sources which flood the wireless systems every day. As video traffic increases, the probability of errors derived from network congestion and interference rises, especially in a wireless network environment. Such factors will negatively impact the video stream quality, leading to diminished Quality of Experience (QoE) for the end user.

Video sequences have different characteristics which describe a different Motion Intensity (MI), such as steady camera sequences (low MI), and panning and zooming sequences (high MI). When losses occur on a high MI frame, video quality will be more degraded than on a frame with less movement. Therefore, videos with a greater MI need better protection than those with a lower one. To preserve the video quality while maximizing the QoE, it is of utmost importance to employ a protection mechanism that can adapt to the video and network's characteristics. Hence, in order to assess the impact of such characteristics in the perceived video quality by humans, QoE metrics must be used.

[1]CNPq Fellow - Brazil

Two commonly used techniques for error recovery are Retransmission and Forward Error Correction (FEC). Retransmission schemes, such as Automatic Repeat Request (ARQ), require a data reception acknowledgement in order to retransmit lost data. This ensures complete delivery of the data but introduces delay which is unsuitable for real-time video transmission over wireless scenarios. If a frame is received after its playout deadline it will be discarded, thus leading to degradation of the video sequence. FEC mechanisms avoid such situations using redundancy to account for errors during transmission. In this way QoE is ensured without the need for retransmission. Nevertheless, FEC mechanisms can be non-adaptive, meaning that the amount of redundancy allocated is fixed and does not account for the variations in the MI characteristics of the video and in the network state. This is a greedy utilization of the already scarce wireless network resources ultimately leading to an aggravation of network traffic congestion due to a disorderly use of redundancy.

On the other hand, to surpass the aforementioned limitations, adaptive FEC mechanisms can be used. These perform Unequal Error Protection (UEP) by allocating different amounts of redundancy to different units of data according to a given rule in their design. Random Neural Networks (RNN) [2] and Ant Colony Optimization (ACO) [3] are dynamic and adaptive mechanisms which enable the use of UEP. Therefore, an adaptive video- and loss-aware mechanism based on RNN and ACO is proposed. The main goal is to improve overall QoE for the end user through the analysis of the video MI parameters and network loss state to adequately allocate an amount of redundancy which minimizes overhead without degrading video quality from the human point-of-view.

The Motion Vectors (MV) are extracted from a video sequence to infer about the MI. They are a crucial part of the compression process of the video, containing information related to nearby frames. By analysing the number of MVs and their Euclidean distance, it is possible to attribute a MI category to the video sequence, hereby allowing the FEC mechanism to use this information during redundancy allocation. The proposed mechanism uses a combination of MV, frame size, and frame type information to categorize motion intensity through a RNN. This is then combined with further information from network losses in a ACO scheme to produce a tailored amount of redundancy suited for each situation.

Neural Networks (NN) are information processing paradigms based on the way biological central nervous systems (e.g., the brain) process data. They can be configured for specific applications through a learning process, comprised of pattern reading and connection weight adjustment following determined rules to produce a desired output. Some common uses of such type of systems, specifically RNNs, are pattern recognition and data classification [4] [5].

The ACO system is a metaheuristic technique which is based on the behaviour of ants in the presence of pheromones. This technique is used to dynamically solve computational problems that can be expressed as path-finding in a graph. From a given starting point on the graph, ants traverse the paths between each node to reach a solution. During each trip, a pheromone marker is deposited. This aids the construction of a solution because the path which has the greater amount of deposited pheromone is a solution for the problem.

The AntMind mechanism processes information on a frame-by-frame basis to adaptively perform QoE-aware data protection, thus being a video-aware UEP scheme. A frame will have a larger amount of redundancy if it is categorized of higher importance and vice-versa. This helps to minimize the impact of overhead on the wireless network as well as preserving the quality of the video, ultimately improving QoE when compared to adaptive and non-adaptive FEC mechanisms.

The remainder of this paper is structured as follows. The related work is presented in Section II. Section III describes the AntMind and its evaluation is presented in Section IV. Conclusions and Future Work are summarized in Section V.

II. Related Work

There has been a growing interest in adaptive FEC mechanisms to improve video quality over wireless networks. This is due to their tailored redundancy allocation from the analysis of characteristics of the video/network without added delay.

Optimized Cross-Layer FEC (OCLFEC) is a Group of Pictures-based (GOP) mechanism which attributes a priority value to the GoP for transmission from the mean squared error of each frame [6]. It uses two error correcting codes, Luby Trasform (LT) and Rate-compatible Parity Check (RCPC). The data is first encoded with LT codes and then redundancy check bits are added to prevent coding errors. These codes are optimized with different parameters for specific situations. The only metric used to assess the performance of the mechanism is Peak Signal-to-Noise Ratio (PSNR) which by itself does not tell much information about QoE. This mechanism does not take into account the MI of the video. This is problematic because the mechanism may have a good Quality of Service (QoS) performance, but this does not mean that QoE is guaranteed. Also the several phases of the mechanism are time consuming which increases delay reducing the overall QoE.

"Transport Audiovisuel avec Protection Ingale des Objets et Contrle d'Admission" (TAPIOCA) is a non MI-based mechanism which divides each GoP by layers and attributes different priority values to them [7]. This enables the distribution of redundancy through the layers of most importance. To assess the performance of the mechanism two metrics were devised, specifically the Decodable Frame Rate (DFR) and the Protection System Efficiency (PSE). These are so unique that they do not provide much information about the QoE performance of the scheme. The process of dividing each GoP into layers is both computationally heavy and time-dependent, making this scheme unsuitable for real-time use.

Adaptive Packet and Block length FEC (APB-FEC) is a non MI-based mechanism which uses packet lengths that are smaller than usual in order to increase the size of the FEC block [8]. It uses packet loss rate feedback information to adapt the video to the network loss characteristics. The metrics used to assess its performance are the network overhead, the effective packet loss rate, and PSNR. However, these do not provide adequate information to evaluate the QoE.

The Video Aware (viewFEC) mechanism is a module-based scheme which analyses MI [9]. It uses an off-line database of several video sequences with MI and complexity information. A heuristic comparison is performed between the GoP and the database to assess the MI of the video being transmitted. The metrics used to assess the performance of the mechanism are suited for a QoE evaluation, but relying too heavily on the database may not provide optimal results when using videos different than those present in it. Also, this mechanism does not rely on packet loss rate information to adapt itself to the current network state while keeping the video QoE high.

The neuralFEC mechanism is a MI based mechanism [10] which performs the categorization of each frame of a video sequence according to its characteristics. It employs a RNN to use the video characteristics to compute an adequate redundancy value in real-time. The metric used to evaluate the performance of the mechanism is Structural Similarity (SSIM). It does not use any type of network loss information, which can introduce unnecessary amounts of added redundancy.

The AntMind mechanism takes into account all the above limitations and improves on them to create a novel QoE-aware adaptive system which provides adequate protection in video distribution over wireless networks.

III. AntMind mechanism

Using the AntMind Mechanism, the aforementioned limitations can be surpassed by taking into account the MI characteristics and the network loss state. Precious wireless network resources are thus spared and the impact of losses is reduced, leading to an overall QoE improvement. Figure 1 shows a general overview of the AntMind mechanism.

Firstly, the off-line training and validation of the RNN created for MI categorization purposes is performed. An exploratory hierarchical cluster analysis using Ward's method for clustering [11] assessed video characteristics and grouped video sequences according to MI. It formed clusters of similar

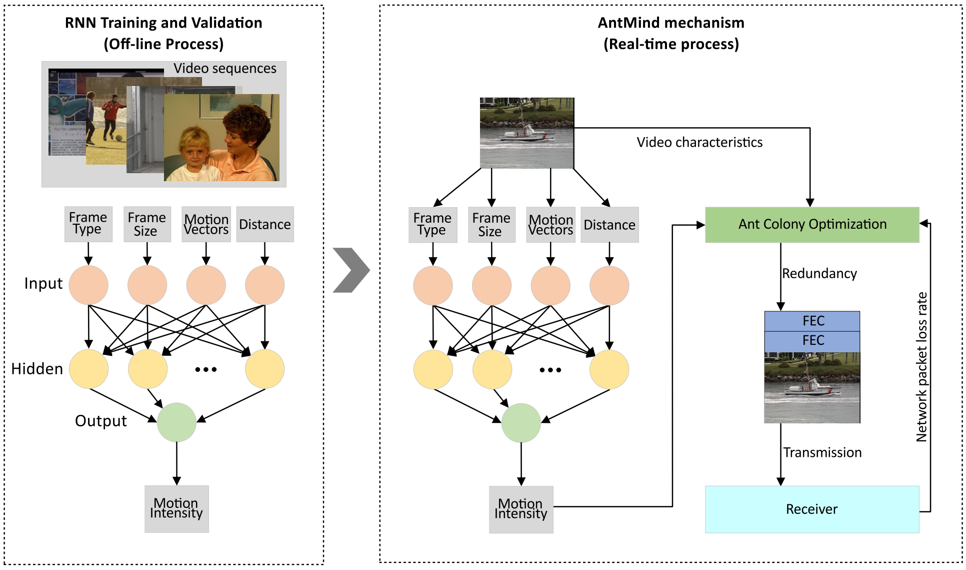

Fig. 1: AntMind mechanism

MIs (Figure 2) from a high intensity of motion to a low intensity. Video characteristics such as frame size, frame type and motion vectors were used during the analysis. From this result, a training set representing video sequences of low motion intensity (Akiyo and Silent), medium motion intensity (City and Football) and high motion intensity (Mobile and Flower) was selected. The RNN was trained using this set so that a different value can be attributed to distinct motion scenarios. After completing its training, the RNN is ready to be used to categorize the videos off-line (i.e., previous to transmission).

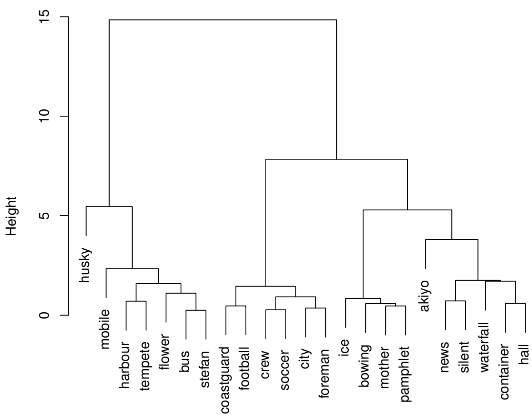

Fig. 2: Hierarchical Clustering of video sequences according to motion intensity

The RNN comprises four input nodes, seven hidden nodes and one output node. The four input nodes represent the video frame's parameters such as frame size, frame type, number of motion vectors and the distance described by those vectors. The single output node represents the computed MI value. Two MV parameters were used due to distinct situations: when a frame has a high number of MVs which have no distance value; when there are fewer MVs but these have higher distance values describing a scenario of greater movement.

Afterwards, the real-time process begins. The network loss information is retrieved from feedback packets sent from the receiver. These contain information representing the rate of erroneous packets in the previously sent frame.

After the identification of the MI characteristics by the RNN and the retrieval of network loss information, the ACO mechanism starts its operation. Based on the RNN assessment and the known characteristics of the video/network, the value representing the amount of redundancy to be used is computed in real-time for each frame. This is done in a way which minimizes wireless network overhead and maximizes QoE.

The graph used for this study, shown by Figure 3, consists of fourteen nodes depicting video and network characteristics. The first node serves as a starting point. Then, the next three nodes represent the classification given by the RNN in terms of MI, namely low, medium, and high. This classification was obtained from the hierarchical cluster analysis' results shown in Figure 2. The following two nodes represent the frame type, I- or P-. The next three nodes depict the frame size as small, medium, and large. The last five nodes represent the network loss rate for the previously transmitted frame.

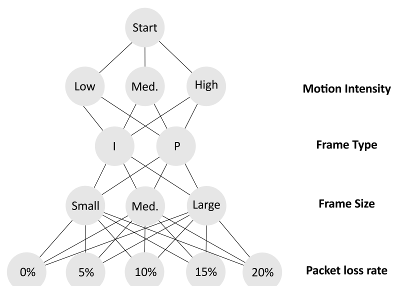

Fig. 3: Graph used in the ACO mechanism

Through the deposition of pheromone in the paths corresponding to the current situation, a preliminary path is generated for the ants. Both the number of iterations and ants is 10 and the simple ACO model was used. The amount of ants and preliminary pheromone was selected through extensive experimentation in order to obtain a plausible solution which did not worsen the processing delay of the AntMind mechanism. During runtime, the ants search the graph while leaving pheromone in the travelled path, resulting in a possible solution for the problem. The results are stored and can be re-used for similar conditions. This avoids re-running ACO again, thus allowing the use of ACO in real-time.

The value computed by the ACO mechanism represents the parameter which will be used in the Reed-Solomon (RS) algorithm [12]. This allows the addition of a specific amount of redundancy according to the video/network characteristics.

RS is of low complexity, resulting in low computational overhead making it suitable for real-time processing of streams of video. The RS code belongs to the family of linear block codes. It converts a source of s bits of an arbitrary length k , into a sequence of n bits of length. In order to protect the data, extra $(n-k)$ bits are added to the original data set. These extra bits are commonly known as parity-check bits.

Through this streamlined process, a tailored amount of protection is allocated to each frame, thus better protecting the most error-sensitive data. The overall QoE and network performance are improved from the minimization of overhead which also reduces the probability for congestion.

Figure 4 shows the AntMind mechanism pseudo-code for each frame. It first retrieves the frame type (02) and checks it against a condition to assess whether it is of type I- or P- (03), as only I- and P- frames will be protected. If a frame is of type B- it is immediately sent (13), otherwise, additional frame characteristics are retrieved, such as frame size (05), number of MVs (06) and the distance pointed by those MVs (07). Then, these characteristics are fed to the RNN for MI categorization (08). From the MI value, the information about the loss rate along with the video characteristics are fed into the ACO mechanism, which computes a value for the parameter of the RS code. This parameter governs the amount of added redundancy (09). Afterwards, RS encodes the data with the RSpar parameter (10) and the frame is sent (11). The packet loss rate is retrieved from feedback information sent from the receiver and the value is updated (15).

```
01 for each Frame
02  FT=getFrameType(Frame)
03  if(FT equal (I- or P-Frame))
04   then
05    FS=getFrameSize(Frame)
06    MV=getMotionVectors(Frame)
07    MVDist=computeDistance(MV)
08    MotionIntensity=RNN(FT, FS, MV, MVDist)
09    RSpar=ACO(MotionIntensity, FT, FS, LR)
10    addRedundancy(RS(RSpar))
11    sendFrame(Frame+Redundancy)
12   else
13    sendFrame(Frame)
14  end if
15 LR=getLossRate(ReceiverFeedback)
16 end for
```

Fig. 4: AntMind pseudo-code

From this accurate classification of the MI characteristics and network loss rate, the adaptive AntMind mechanism can minimize overhead. It does so while preserving the quality of the video. Therefore, it reduces the footprint of video transmission on the network while improving overall QoE.

IV. Performance Evaluation and Results

The main goal of AntMind is to improve the use of wireless network resources through the reduction of the network overhead derived from the allocation of redundancy by FEC mechanisms while assuring QoE. The performed evaluation aims at showing that the AntMind mechanism can effectively reduce network overhead while preserving video quality. A wireless mesh network scenario was devised, consisting of 25 nodes disposed on a 5 by 5 grid with a distance of 50 meters between them. The Network-Simulator 3 (NS-3) [13] was used to perform the evaluation of the proposed mechanism. The Optimized Link State Routing Protocol (OLSR) [14] was used as the routing protocol. The data set consisted of ten video sequences with different characteristics. These videos represent content commonly found in on-line video services. The video sequences are coded with the H.264 video codec and are in the Common Intermediate Format (CIF). Furthermore the sequences have a GoP of 19 with two B-frames after each I- and P- frames.

With the objective to describe the burst loss patterns of a wireless network [15], a two-state discrete-time Markov chain model following the Gilbert-Elliot packet-loss model [16] was implemented. The simplified Gilbert-Elliot packet-loss model consists of two nodes representing G, a Good state where no packets are lost, and B, a Bad state where all the packets are lost. These two states are connected by the probability of transitioning from G to B P_{GB} and the probability of transitioning from B to G P_{BG}. By adjusting these probabilities we can obtain different patterns of error which represent specific Packet Loss Rate (PLR) values (5%, 10%, 15%, and 20%) commonly present in wireless networks.

In order to thoroughly assess the results provided by AntMind, four distinct data protection schemes were used, namely one without protection, one with non-adaptive protection and two with adaptive protection. The first scheme is used to obtain a baseline value, to further assess the improvements of the FEC mechanisms. The second and third schemes are Video-aware Equal Error Proctecion (VaEEP) and Video-aware UEP (VaUEP) respectively. In the VaEEP mechanism a fixed amount of redundancy is added I- and P- frames. In the VaUEP mechanism, the same frames are protected with different fixed amounts of redundancy depending on the frame type. The protection of only I- and P- frames is a common practice in video transmission. The redundancy amounts were attained after a thorough set of simulation studies, where the best possible trade-off regarding the amount of redundancy and QoE in terms of video quality was found. This translates into a value of 38% average added redundancy for VaEEP and of 30% for VaUEP. The proposed mechanism (AntMind) is the last scheme used consisting in a combination of an RNN and ACO for Unequal Error Protection.

Two objective QoE metrics were employed [17], namely the Structural Similarity (SSIM) Index and the Video Quality Metric (VQM). The SSIM analyses luminance, contrast and structural similarity of images to assess the similarity/likeness of the pictures. VQM is a Discrete Cosine Transform (DCT)-based metric which uses the spatial-temporal property of the human visual system's perception to assess the distortion of the pictures. In SSIM, higher values represent better video quality, while in VQM lower values represent higher video quality. To enable the objective evaluation of video quality two tools were used, namely EvalVid [18] and the MSU Video Quality Measurement Tool (VQMT) [19].

The selected sequences are different from those used to train the RNN in order to guarantee that the mechanism will function with any other random video sequence, thus ensuring the validity of the classification performed by it.

Table I shows the results in terms of the average added overhead of all PLRs using the three FEC schemes. VaEEP's overhead ranged from 35% to 43% averaging at 38%, and VaUEP's added overhead ranged from 25% to 36% averaging at 30%. AntMind's overhead ranged from 9% to 19% averaging at 15%. This means that in some cases the reduction of added overhead reached 77% over VaEEP and 72% over VaUEP. Therefore, far less redundancy data is used by the AntMind opposed to VaEEP and VaUEP translating into reductions of 61% and 50%, respectively.

From the results, it is shown that the AntMind mechanism assesses the importance of frames according to their MI characteristics. Therefore, attributing a less redundancy to videos with a lower MI and a more redundancy to videos with a higher MI. This is clearly observable for Bowing and Mother which are categorized as low MI video sequences versus Coastguard, Harbour and Container which are categorized as high MI video sequences. Additionally, in the Mother and Soccer video sequences, the VaEEP mechanism allocates a higher amount of redundancy to Mother (41%) than to Soccer (36%). In Mother, the proportional size of I- and P-frames is higher than that of the B- frames due to its low MI. In Soccer, this is not valid because it has a higher MI. Therefore, our mechanism allocated a higher amount of redundancy to Soccer (16%) in contrast to Mother (9%).

TABLE I: Average Overhead

	VaEEP	VaUEP	AntMind
Bowing	42%	36%	10%
Coastguard	37%	27%	19%
Mother	41%	33%	9%
Soccer	36%	27%	16%
Hall	35%	27%	13%
Container	43%	35%	18%
Crew	35%	25%	16%
Foreman	37%	28%	15%
News	43%	35%	17%
Harbour	36%	26%	18%
Overall	38%	30%	15%

The SSIM and VQM metrics were used to perform the evaluation of the AntMind mechanism in order to complement the results obtained for the added overhead and to ensure that video quality was preserved. The different observable values are due to each video sequence's uniqueness, highlighting the importance of performing the experiments with video sequences with a broad array of MI levels/characteristics.

Figure 5 shows the values obtained in terms of SSIM for each of the schemes and for all of the video sequences. The average SSIM value was computed from all the video sequences for all PLRs. The mechanism without FEC averaged a value of 0,805. The VaEEP and VaUEP mechanisms obtained values of 0,881 and 0,882, respectively, which are closely matched by a value of 0,876 obtained for the adaptive AntMind mechanism.

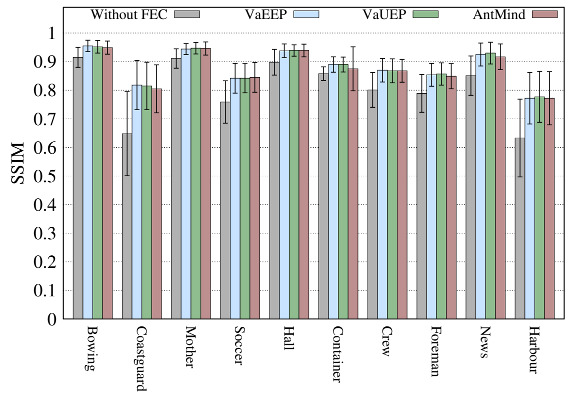

Fig. 5: Objective QoE assessment (SSIM)

Analysing in further detail the Coastguard video sequence in Table II, for a higher PLR the SSIM scores are considerably worse than for a lower PLR. The Mother video sequence does not show this kind of behaviour between distinct PLRs. Such reduction of quality is of course expected due to the increased PLR. Nevertheless, a change of such magnitude as observed for Coastguard and Harbour means that packet loss has a greater impact on video sequences which have a higher intensity of motion, contrary to Mother and Bowing. This shows that video sequences with a lower intensity of motion have a greater resilience towards loss.

TABLE II: SSIM variation through the PLR

	Without FEC		AntMind	
	Coastguard	Mother	Coastguard	Mother
PLR 20%	0,482	0,868	0,688	0,915
PLR 15%	0,574	0,899	0,784	0,938
PLR 10%	0,678	0,923	0,841	0,959
PLR 5%	0,859	0,955	0,906	0,971

Figure 6 shows the VQM results. The VaEEP and VaUEP mechanisms achieved an average VQM of 3,895 and 3,860, respectively, while the adaptive AntMind mechanism obtained an average of 3,940, meaning that video quality was maintained. These results follow a trend similar to that of SSIM. This helps corroborate the improvements of the proposed mechanism in overhead reduction with video quality shielding.

Table III summarizes the SSIM, VQM, and network overhead results. It shows that the proposed adaptive mechanism managed to achieve a considerable reduction in network

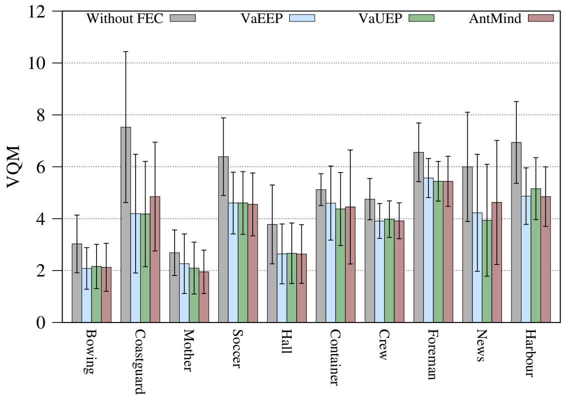

Fig. 6: Objective QoE assessment (VQM)

overhead by avoiding the addition of unnecessary redundancy. Furthermore, it did so while preserving video quality. This is of great importance in wireless network environments due to their limited network resources.

TABLE III: Average SSIM, VQM and network overhead

	AntMind	VaEEP	VaUEP	Without FEC
SSIM	0,876	0,881	0,882	0,806
VQM	3,940	3,895	3,860	5,278
Overhead	14,898%	38,460%	29.827%	–

Overall, the results showed that the AntMind mechanism can considerably reduce network overhead. It does so by performing an accurate classification of the MI components of the video. This information is used in conjunction with network loss state information to dynamically allocate redundancy on a frame-by-frame basis. By doing so, it ensures adequate protection of video sequences with different MIs while preserving video quality.

V. Conclusion and Future Works

The growing interest in video streaming on the go increases the stress upon the existing wireless networks. To make an efficient use of the resources while ensuring video quality, adaptive FEC mechanisms must be used. The AntMind mechanism performs a dynamic protection of the data that impacts QoE the most. Video quality is preserved while greatly reducing the use of network resources. The footprint and benefits of the AntMind scheme were demonstrated through a set of experiments using real video sequences.

The simulation results evidenced interesting behaviours from some video sequences, showing that those with a higher amount of MI require more protection. The AntMind mechanism uses MI and network loss to adequately shield a video stream with changing video characteristics in a lossy wireless network. It reduced network overhead by 61% on average, showing an improvement over non-adaptive and adaptive FEC mechanisms. Future improvements should further enhance of the mechanism considering other video sequences and the position of frames inside the GoP. Mobility and cross-talk scenarios should be explored to assess the performance of the mechanism under such conditions.

Acknowledgment

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

References

[1] comScore, “2013 europe digital future in focus,” comScore, WhitePaper, March 2013.

[2] A. Abraham, “Artificial neural networks,” *handbook of measuring system design*, 2005.

[3] M. Dorigo, V. Maniezzo, and A. Colorni, “Ant system: optimization by a colony of cooperating agents,” *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on*, vol. 26, no. 1, pp. 29–41, 1996.

[4] S. Mohamed and G. Rubino, “A study of real-time packet video quality using random neural networks,” *Circuits and Systems for Video Technology, IEEE Transactions on*, vol. 12, no. 12, pp. 1071–1083, 2002.

[5] E. Aguiar, A. Riker, A. Abelém, E. Cerqueira, and M. Mu, “Video quality estimator for wireless mesh networks,” in *Quality of Service (IWQoS), 2012 IEEE 20th International Workshop on*. IEEE, 2012, pp. 1–9.

[6] A. Talari, S. Kumar, N. Rahnavard, S. Paluri, and J. Matyjas, “Optimized cross-layer forward error correction coding for h.264 avc video transmission over wireless channels,” *EURASIP Journal on Wireless Communications and Networking*, vol. 2013, no. 1, pp. 1–13, 2013.

[7] V. Lecuire, “Unequal error protection under bitrate constraint for video streaming over internet,” *Computer Communications*, vol. 35, no. 3, pp. 287 – 297, 2012.

[8] M.-F. Tsai, N. Chilamkurti, and C.-K. Shieh, “An adaptive packet and block length forward error correction for video streaming over wireless networks,” *Wireless Personal Communications*, vol. 56, no. 3, pp. 435–446, 2011.

[9] R. Immich, E. Cerqueira, and M. Curado, “Cross-layer fec-based mechanism for packet loss resilient video transmission,” in *Data Traffic Monitoring and Analysis*, ser. Lecture Notes in Computer Science, E. Biersack, C. Callegari, and M. Matijasevic, Eds. Springer Berlin Heidelberg, 2013, vol. 7754, pp. 320–336.

[10] R. Immich, P. Borges, E. Cerqueira, and M. Curado, “Adaptive motion-aware fec-based mechanism to ensure video transmission,” in *19th IEEE Symposium on Computers and Communications*, 2014.

[11] J. H. Ward Jr, “Hierarchical grouping to optimize an objective function,” *Journal of the American statistical association*, vol. 58, no. 301, pp. 236–244, 1963.

[12] I. S. Reed and G. Solomon, “Polynomial codes over certain finite fields,” *Journal of the Society for Industrial and Applied Mathematics*, vol. 8, no. 2, pp. 300–304, June 1960.

[13] G. F. Riley and T. R. Henderson, “The ns-3 network simulator modeling and tools for network simulation,” in *Modeling and Tools for Network Simulation*, K. Wehrle, M. Güneş, and J. Gross, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2010, ch. 2, pp. 15–34.

[14] T. Clausen, P. Jacquet, C. Adjih, A. Laouiti, P. Minet, P. Muhlethaler, A. Qayyum, L. Viennot *et al.*, “Optimized link state routing protocol (olsr),” 2003.

[15] L. Wilhelmsson and L. B. Milstein, “On the effect of imperfect interleaving for the gilbert-elliott channel,” *Communications, IEEE Transactions on*, vol. 47, no. 5, pp. 681–688, 1999.

[16] R. Razavi, M. Fleury, and M. Ghanbari, “Adaptive packet-level interleaved fec for wireless priority-encoded video streaming,” *Adv. MultiMedia*, vol. 2009, pp. 3:1–3:14, Jan. 2009.

[17] S. Chikkerur, V. Sundaram, M. Reisslein, and L. Karam, “Objective video quality assessment methods: A classification, review, and performance comparison,” *Broadcasting, IEEE Transactions on*, vol. 57, no. 2, pp. 165–182, 2011.

[18] J. Klaue, B. Rathke, and A. Wolisz, “Evalvid - a framework for video transmission and quality evaluation,” in *In Proc. of the 13th International Conference on Modelling Techniques and Tools for Computer Performance Evaluation*, 2003, pp. 255–272.

[19] D. Vatolin, A. Moskvin, O. Petrov, S. Putilin, S. Grishin, and A. Marat. (2011) Video quality measurement tool. Moscow State University.