Adaptive Motion-aware FEC-based Mechanism to Ensure Video Transmission

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***Abstract*—Video transmission over wireless networks has shown a great increase in recent years and it is becoming part of our daily life. Meanwhile, several difficulties can impair the success of the transmission, such as limited network resources, high error rates and fluctuating signal strength that may lead to variable bandwidth. Therefore there is the need for adaptive mechanisms that can provide a good video transmission. Adaptive Forward Error Correction (FEC) techniques which assure Quality of Experience (QoE) are a convenient means of delivering video data to wireless users in dynamic and error prone networks, while taking into account the content of the transmitted data. This paper proposes an adaptive content-aware and Random Neural Network (RNN) based mechanism to provide protection of real-time video streams against packet loss in wireless networks, improving user experience and optimising network resources. The benefits of the proposed mechanism are demonstrated through simulations and assessed with QoE metrics.**

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

I. Introduction

In the last few years the use of real-time video services in wireless and mobile networks has seen a dramatical increase [1], namely in Europe where the growth in mobile video views was of 162% from 2011 to 2012. The outlook for growth, according to Cisco, is even greater and will represent over 90% of the global IP traffic by 2015 [2]. This viewpoint can be explained by the substantial amount of new forms of entertainment and information, which include news websites, social networking communities, e-learning as well as large amounts of user-generated content.

Due to the video traffic growth, it becomes critical to improve its transmission quality. However, the network resources are not unlimited, and therefore, many factors, such as propagation loss, congestion, and channel noise, can hinder the transmission. This may cause packet loss which in turn degrades video quality and negatively impacts the end user experience. The quality of the video should be assessed in terms of Quality of Experience (QoE), because contrary to Quality of Service (QoS), it assesses the quality of the video as perceived by the end user. Therefore, QoE must be considered in the process of building a mechanism that can adapt to the video and network characteristics.

An adaptive mechanism is needed to combat the information loss on networks with different characteristics. This mechanism should improve the video transmission to ensure that the viewing experience of the users is not negatively affected by the impairing factors of the wireless environment. Retransmission and Forward Error Correction (FEC) are two commonly used techniques to handle network limitations. Retransmission mechanisms are suitable for systems where delivery must be guaranteed. However, in a real-time video transmission environment, what is most important is the timely delivery of the content, because if a frame arrives after its decoding deadline it can no longer be displayed. On the other hand, FEC mechanisms have delay-constraints. These mechanisms add redundancy to the original data so that it is possible to correct, without retransmission, eventual errors or losses caused due to the characteristics of the network. The problem is that many times they are non-adaptive and strict. This means that the mechanism only offers a fixed amount of protection/redundancy to the data to be transmitted, not taking into account the video characteristics. This can lead to a poor utilization of network resources and it can cause network congestion due to unnecessary overhead.

Taking these problems into account, this paper proposes a novel adaptive Video-aware Random Neural Networks (RNN) based mechanism (neuralFEC). It aims at overcoming the limitations of non-adaptive schemes, such as the inability to take into consideration the video's motion intensity, which is crucial to a high QoE. An efficient way to quantify the motion intensity is through Motion Vectors (MV). These vectors play a key part in the video compression process, allowing to store changes from adjacent frames, including both previous and future frames. Therefore it is possible to quantify the motion intensity of a given frame using the information inside his MV. The proposed mechanism mitigates these problems by adaptively selecting the amount of redundancy given to individual frames, through the analysis of their type and their motion characteristics through a RNN [3]. Neural networks (NN) are computational models inspired by biological central nervous systems, which are able to go through the process of machine learning and pattern recognition. They can be trained by feed-

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ing them with learning patterns and letting them change the weights according to some learning rule. The choice of RNN is related to their particular characteristics that enable their success in pattern recognition and classification problems [4].

Another important feature of neuralFEC is the use of a Unequal Error Protection (UEP) scheme. This allows the use of different amounts of redundancy to different parts of the data. The proposed UEP scheme protects frames with a greater intensity of movement with a larger amount of redundancy opposed to those with lower intensities of movement. This scheme reduces network overhead through the adaptive and selective use of redundancy while also improving or at least maintaining the level of QoE of the transmitted videos when compared to 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 neuralFEC and its evaluation is presented in Section IV. Conclusions and Future Work are summarized in Section V.

II. Related Work

Adaptive FEC mechanisms have been gaining an increased interest because they allow for the redundant data to be used according to the video and network characteristics. The APB-FEC scheme aims to solve the problem of conventional packet level FEC by the use of a smaller packet length, while increasing the FEC block length [5]. By using feedback information from the receiver regarding the correct reception of the packets, the mechanism adapts the video in the streaming buffers to the network conditions. The use of buffers is not optimal and can increase the delay. Also, relying on information from the receiver can be problematic due to the fact that if the communication is hindered it is very probable that the feedback information will not reach the sender.

The ViewFEC module-based mechanism [6] uses a database module with motion and complexity information from several videos that is built prior to video distribution. It also uses another module to assess the length of the Group of Pictures (GoP) which has a greater influence in the received video quality if packets are lost during transmission. The motion intensity classification adopts a heuristic based comparison with the database, which may lead to non-optimal results.

Another FEC mechanism uses a layer-based approach which processes each GoP and divides it into layers of different utility to adequately distribute FEC among them [7]. This process is very time consuming and takes more time with larger GoP sizes, which in turn adds delay to the transmission. If the layer-division is not already processed, this mechanism requires a great amount of processing which means it cannot be used in real-time video transmission.

Also related to the use of GoP information is the optimized cross layer FEC mechanism which assigns different priorities to the GoPs according to the commutative mean squared error of the entire GoP [8]. The GoPs are encoded and cyclic redundancy check bits are added to detect coding errors. Afterwards the FEC codes are optimized with different parameters for different situations. This mechanism has several optimization phases, for each frame, that are very time consuming, increasing the delay and degrading the QoE.

III. Adaptive mechanism

The issues presented above, together with the need to further optimize the use of network resources, make way for the novel mechanism proposed in this paper. The neuralFEC goal is to use an optimized UEP scheme according to the video frame's motion intensity characteristics. Making it possible to better protect the most QoE-sensitive frames, therefore providing both, the reduction on the impact of packet loss on the video quality and the use of only the necessary amount of redundancy. Through this, it is possible to distribute the redundancy in a way that will improve the QoE for the end user while sparing precious network resources.

Figure 1 depicts the overall operation of the neuralFEC mechanism. First of all, in the offline process, an exploratory analysis using hierarchical clustering was carried out to train the RNN. Through the human experience about the intrinsic video characteristics and several simulation experiments the RNN was also validated. After this, the RNN can be used in real-time. The offline process is very important because it leads to accurate results in real-time. Then the decision making process conducted by the RNN determines a specific amount of redundancy needed by each frame. This allows the neuralFEC to shield only the QoE-sensitive data against packet loss, resulting on better video quality as perceived by the end-users while saving network resources. A detailed explanation of the proposed mechanism is presented afterwards.

In order to perform the classification of each frame according to its motion intensity a RNN was employed. As other NNs, this model has the capability for learning and generalization, but excels in pattern recognition and classification problems [4]. By training the network successfully with an adequate range of video samples, it can be used in real-time to classify a given video sequence according to the intensity of the movement. This is achieved by attributing a specific value to determine frames with different motion intensities. After that, the neuralFEC is able to select in real-time the appropriate amount of redundancy to be transmitted so that the network overhead is minimized and QoE is maximized.

The RNN structure consists of three input nodes, seven hidden layer nodes and one output. The three input nodes represent each frame's characteristics specifically frame size, frame type, and MV ratio (total number of motion vectors divided by the distance described by them). The MV in a video sequence was adopted from the classical mechanics and vector-oriented model of motion used by them. This is a simple model that defines the movement of objects as the progression of small translations on a plane. A MV ratio was used because a certain frame can have several vectors pointing to a close distance while other frames can have less vectors pointing further away however, and consequently defining a situation of higher motion intensity. Finally, the output node provides the motion intensity classification value, computed by the network from the given inputs. Through these parameters it is possible

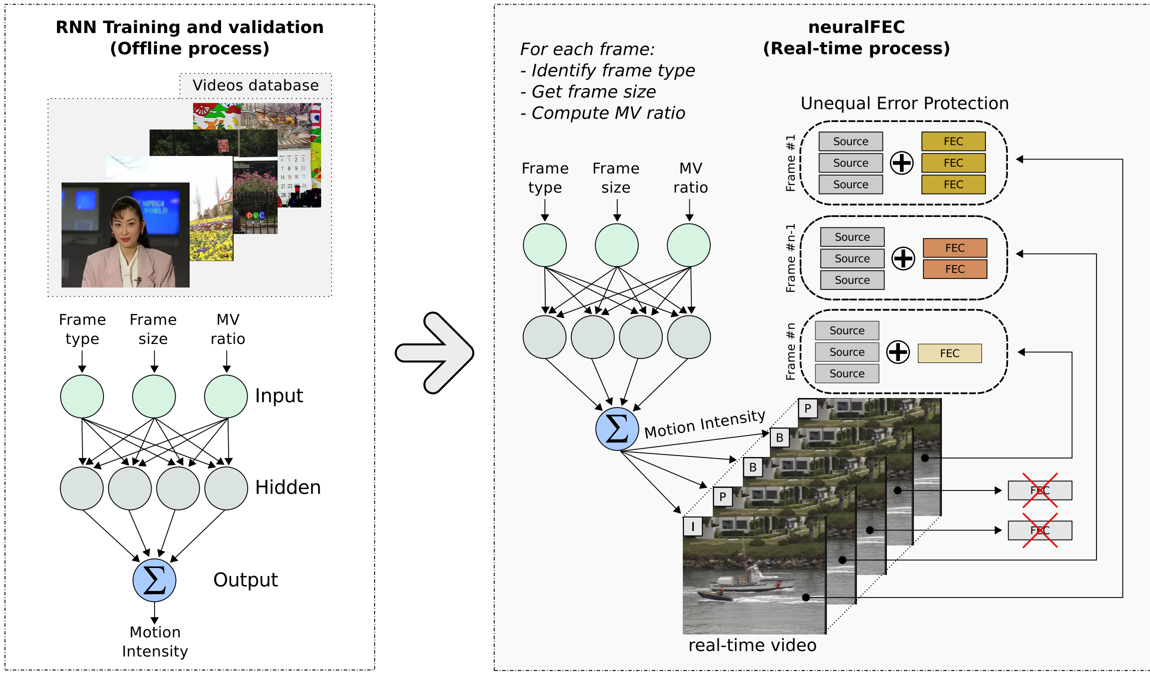

Fig. 1. neuralFEC mechanism

to characterize the video motion intensity and choose the optimal amount of redundancy on a frame-by-frame basis.

To adequately train the RNN, an exploratory hierarchical cluster analysis using Ward's method [9] was performed to categorize selected video sequences which represent different types of movement. The video sequences were selected according to the recommendations of the Video Quality Experts Group (VQEG) [10] and the International Telecommunications Union (ITU) [11], and represent sequences that cover different distortions and content that are commonly seen in online videos. A set of 15 videos was selected to perform the hierarchical cluster analysis. Each video was broken down into three parameters, namely about the frame size and type, and the total number of motion vectors divided by the distance described by these vectors.

Using the exploratory analysis results, the video sequences were classified into three categories of motion intensity, namely low, median and high intensity. Afterwards, two videos of each motion intensity category were randomly selected to train the RNN. The training of the RNN consisted in feeding the information of this set of selected videos to the inputs of the network for about 600 iterations which was the point at which the Minimum Mean Squared Error (MSE) stabilized. After the training of the RNN was completed, the RNN was validated with a different set of video sequences, the remaining 9 videos from the exploratory analysis, which also cover all three motion intensity characteristics. The results obtained proved to be correct classifications of the video sequences present in the validation set.

After the training and validation phases, the RNN can be used in the real-time process. Using cross-layer techniques, the neuralFEC is able to obtain important information about several video characteristics, namely frame type and size, as well as the number of motion vectors and the Euclidean distance pointed by them. All these details are fed to the RNN which in turn provides, in real-time, an accurate motion intensity value for each frame. After the video frame is classified it is encoded by the Reed-Solomon (RS) [12] with the amount of redundancy selected by the RNN. This erasure code has low complexity, and therefore provides better performance for real-time services [13]. The RS is a linear block code that has a rule to convert of source bits s, of length k, into a transmitted sequence t of length n bits. To add redundancy, n is made greater than k. In a linear block code, the extra $(n-k)$ bits are linear functions of the original k bits, which are called parity-check bits. It allows us to use different block sizes represented by each individual frame. Through this procedure, a precise UEP amount can be assigned to each frame, where only the QoE-sensitive data will be protected. In turn, this results in better video quality while reducing the amount of redundancy data needed, thus not adding unnecessary the network overhead. This reduction is very important because it can be the source of serious interference problems. In this way, not adding unnecessary redundancy will allow more users to access services with better QoE, improving the overall system performance.

Figure 2 shows the pseudo-code portraying the neuralFEC real-time operation. All procedures are performed inside a for-loop, at line 01, which will go through all the frames in the video sequence. At line 02, the frame type is identified to be used in the selection control mechanism (if statement) at line 03. This allows the change in the control flow according to neuralFEC needs, which is, to assign a tailored redundancy amount to I- and P-Frames, and send B-Frames without additional data. At lines 05, 06, 07, and 08 it is possible to observe the identification of the frame size, the computation of the MV ratio, the classification of the video frame motion intensity using the RNN, and the assignment of an unequal amount of redundancy to the most QoE-sensitive data, respectively. Lines 09 and 11 are responsible for sending the frame with or without redundancy.

```
01 for each Frame
02  FT=getFrameType(Frame)
03  if(FT equal (I- or P-Frame))
04   then
05    FS=getFrameSize(Frame)
06    MVratio=calculateRatio(getMV(Frame))
07    MotionIntensity=RNN(FT, FS, MVratio)
08    addRedundancy(RS(MotionIntensity))
09    sendFrame(Frame+Redundancy)
10   else
11    sendFrame(Frame)
12  end if
13 end for
```

Fig. 2. neuralFEC pseudo-code

IV. Performance Evaluation and Results

The main objective of the neuralFEC is to reduce the network overhead by not adding unnecessary redundancy while having a light improvement or at least maintain the same video quality. In order to assess the performance of the proposed mechanism in wireless networks, several experiments were performed using Network-Simulator 3 (NS-3) [14]. The scenario for evaluation is comprised of 25 nodes in a grid disposition (5x5), separated by 50 meters. The Optimized Link State Routing Protocol (OLSR) [15] was used as the routing protocol. Ten video sequences were used in this scenario, namely Bowing, Coastguard, Container, Crew, Foreman, Hall, Harbour, Mother and Daughter, News and Soccer. These particular sequences were selected in order to have a great variety of motion intensities. They are in Common Intermediate Format (CIF) with a resolution of (352x288) and coded with the H.264 codec. The GoP size was set to 19 and after each I- or P-frames, come two B-frames.

A two-state discrete-time Markov chain model was implemented following a simplified Gilbert-Elliot packet-loss model [16], which approximates the behaviour of a wireless network. It produces simulation results which are closely related to those of burst loss patterns of wireless channels [17]. The simplified Gilbert-Elliot is shown in Figure 3, where the probability of packet loss in the Good state (G) was set at 0, which means no losses, and the probability of packet loss in the Bad state (B) was set at 1, where all packets are lost. The Packet Loss Rate (PLR) can be obtained by Equation 1, where P_{BG} represents the probability of transitioning from the Bad state to the Good state and vice-versa with P_{GB}.

$$PLR = \frac{P_{BG}}{P_{BG} + P_{GB}} \tag{1}$$

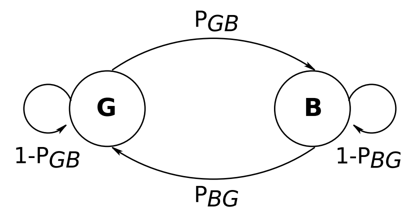

Fig. 3. Gilbert-Elliot simplified model

To validate and compare the results, three experiments with different schemes were performed. The first experiment serves as a baseline as there was no FEC mechanism in use. The second experiment was performed with a non-adaptive video-aware FEC mechanism (Video-aware FEC), where a fixed amount of 38% of redundancy was added only to I- and P-frames. This amount of redundancy was selected according to an extensive set of experiments, which showed the best video quality situation taking into consideration the characteristics of the scenario defined for the experiment. The last experiment is the proposed adaptive mechanism with RNN and UEP (neuralFEC). Each of the three experiments was simulated 10 times with an error rate of 20% representing an average loss [18] obtained through the simplified Gilbert-Elliot model.

The video quality of each evaluation scenario was assessed through an objective measurement, namely the Structural Similarity (SSIM) Index. This objective evaluation metric is a method based on the analysis of luminance, contrast and structural similarity of images. SSIM is one of the most commonly used metrics for objective evaluation of QoE [19]. The objective quality assessment of the video sequences was performed with EvalVid [20] and the MSU Video Quality Measurement Tool (VQMT) [21].

A set of ten video sequences different from those used to train the RNN was used. They represent distinctive situations with a broad type of motion intensity characteristics. Three different mechanisms were used to perform the experiments on the mentioned sequences, namely without protection, with the non-adaptive Video-aware FEC mechanism and finally with the adaptive neuralFEC mechanism.

Figure 4 shows the results in terms of overhead of the experiments. While using the non-adaptive Video-aware FEC mechanism the network overhead added was between 35% and 43%. On the other hand, when the neuralFEC mechanism was employed the amount of overhead remained between 13% and 24%. This means that the average redundancy added by the non-adaptive mechanism was around 38% on contrast to only 19% added by neuralFEC. It is also clear that the proposed mechanism can assess the importance of frames according to motion intensity. This assessment is performed by the RNN, which attributes a higher classification for frames with a great amount of movement, and a lower classification for frames with less amount of movement. In doing that, a greater amount of redundancy was attributed to video sequences such as Crew, Soccer, Harbour and Coastguard. On

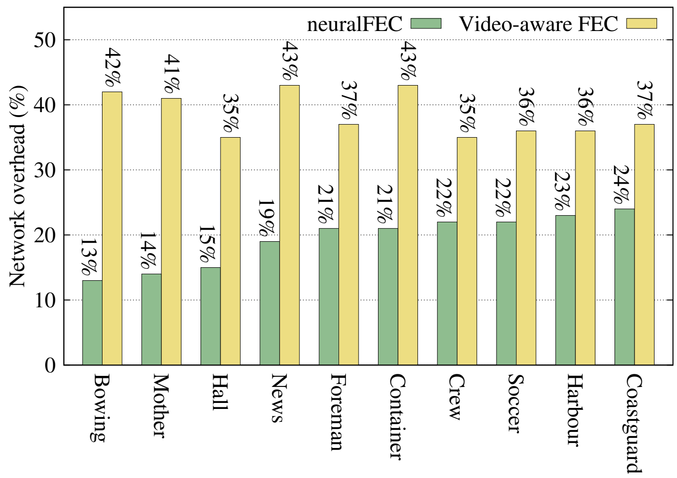

Fig. 4. Network Overhead

the contrary, video sequences which are classified as being of lesser motion intensity, such as Bowing, Mother and Hall are given less redundancy. These results show that the neuralFEC mechanism performs better than the non-adaptive Video-aware FEC mechanism in terms of overhead, by reducing in average a half of the redundancy needed to protect the data.

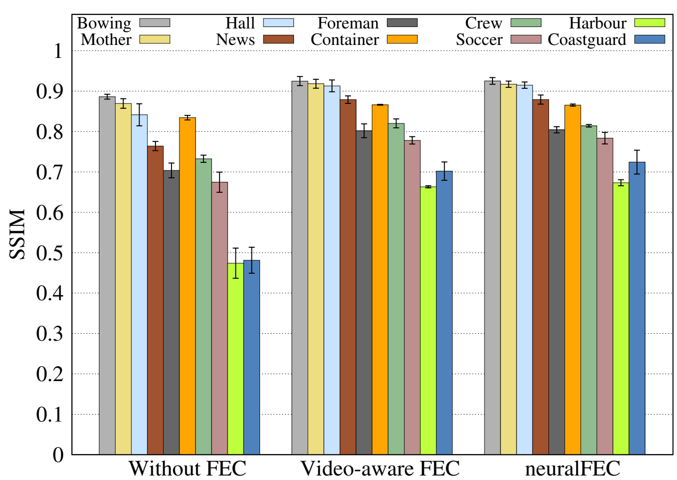

Fig. 5. Objective QoE assessment (SSIM)

Besides saving the already scarce network resources by not adding unnecessary redundancy, it is also important to provide good video quality. In order to verify this situation, a set of assessments were performed using the SSIM metric. Figure 5 depicts the SSIM values for each video sequence while using the three aforementioned protection schemes. The results show the neuralFEC mechanism obtained an average SSIM value of 0,831 against a value of 0,819 for the video-aware FEC mechanism and 0,726 for the mechanism that did not use any type of protection. This represents a slight improvement of almost 1,5% , on average, in terms of SSIM value for the adaptive neuralFEC mechanism in comparison to the non-adaptive video-aware FEC mechanism. In further detail, the SSIM score achieved by neuralFEC for the Harbour video sequence was of 0,675 against 0,662 for the video-aware mechanism and 0,485 for the mechanism without FEC. Although all video were transmitted with the same PLR, the SSIM score obtained by the same three mechanisms for the Bowing sequence was of 0,915, 0,914 and 0,920 respectively. This can be explained by the different characteristics of these two sequences. The Harbour video sequence has a greater amount of motion compared to the Bowing sequence, meaning that packet loss has a greater effect on this type of sequences. This results in lower SSIM scores for sequences with a higher degree of motion intensity, and also shows that videos with a lower degree of motion intensity have greater resilience to packet loss. Due to this, it is important to employ adaptive FEC mechanisms, such as neuralFEC to protect the contents of the video taking into account its motion intensity characteristics.

TABLE I
AVERAGE SSIM AND NETWORK OVERHEAD

	neuralFEC	**Video-aware FEC**	**Without FEC**
SSIM	0,831	0,819	0,726
Overhead	19,334%	38,460%	–

Table I summarizes the results presenting the average SSIM and network overhead for all video sequences. It demonstrates that the proposed neuralFEC mechanism had a slightly improved video quality. Most importantly, it was able to do so while drastically reducing the network overhead by not adding unnecessary redundancy. This is of great importance in wireless networks, due to the limited nature of the wireless channel resources, which can be aggravated by packet loss due to interference from concurrent transmissions and network congestion.

The results showed that the neuralFEC mechanism, through an accurate motion intensity classification of video sequences with distinct characteristics, is able to add a precise amount of protection. In doing that, it can offer less overhead during transmission in a wireless mesh network setting while providing as good video quality as non-adaptive FEC mechanisms.

V. CONCLUSION AND FUTURE WORKS

The growth of the online video transmission over wireless networks calls for adaptive QoE-aware mechanism to ensure the video quality. To fill this gap, the neuralFEC provides the possibility to shield the video transmission in wireless networks, protecting only the most QoE-sensitive data, maximizing the video quality while saving network resources by not sending unnecessary redundancy. This is important to better use the already scarce wireless resources. Both impact and advantages of the neuralFEC approach were demonstrated through a set of experiments using real video sequences.

The experimental simulation results showed that neuralFEC was able to highly reduce the amount of network overhead by 50% while maintaining or even improving the QoE for the end user. This is a great enhancement over non-adaptive FEC mechanisms and also reinforces the importance of using adaptive FEC mechanisms which take into account motion intensity when protecting a video stream with varying characteristics. Future work should emphasize further refinement of the mechanism by taking into account a larger set of video sequences. Additionally, other adaptive FEC mechanisms will be used to evaluate the performance of neuralFEC. Different scenarios should be explored by introducing mobility and cross-traffic to assess the resilience of the mechanism in such conditions.

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