Ensuring QoE in Wireless Networks with Adaptive FEC and Fuzzy Logic-based Mechanisms

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***Abstract*—Online video transmissions over wireless networks are rising in popularity and have already become part of our daily life. In the meantime, it is necessary to address a number of challenges ranging from the scarce resources, time-varying, and high error rates, to the fluctuating bandwidth, unveiling the need for an adaptive mechanism to ensure a good video transmission. Adaptive Forward Error Correction (FEC) techniques with Quality of Experience (QoE) assurance are appropriate to deliver QoE-aware video data to wireless users in dynamic and high error rates networks. This paper proposes an adaptive Video-aware FEC and Fuzzy Logic-based mechanism to shield real-time video transmissions against packet loss in wireless networks, improving both user experience and the usage of resources. The benefits and drawbacks of the proposed mechanism compared with exiting work are demonstrated through simulations and assessed with QoE metrics.**

***Index Terms*—Forward Error Correction (FEC) ; Video-aware FEC; Fuzzy Logic; QoE; Cross-layer; Unequal Error Protection (UEP)**

I. Introduction

The consumption of online videos has been increasing rapidly in recent years, especially from wireless mobile devices. Following the same trend, several companies are making use of this technology to improve collaboration, reduce costs, and increase productivity. Apart from that, the number of non-professional users producing, sharing, and accessing online videos is growing apace. As an example, only in December 2012 more than 1.2 billion of unique worldwide users viewed some type of online videos [1]. This means that over 83% of the Internet users are making use of this sort of content.

The perception of live videos, characterized in terms of Quality of Experience (QoE) [2], is directly measured by the acceptability of the users and is related to, but differs from the extensively studied concept Quality of Service (QoS). The use of QoE quantifies how the video quality is perceived from the user side and must be included in QoE-aware networking adaptation schemes, especially in dynamic wireless environments with high error rates.

Wireless channel conditions can quickly fluctuate over time owing to the mobile host movement, multipath fading, noise, and also, co-channel interference. In contrast with the wired links, packet loss does not necessarily mean network congestion, and can often be related to random physical causes, leading to time-varying communication impairments, and recurring link interruptions [3]. One of the challenges in wireless systems is how to adapt and optimize the distribution of real-time videos with QoE support in dynamic wireless environments. The adoption of an adaptive redundancy control mechanism with human- and video-awareness is a key element to make an efficient use of resources preventing the induction of network congestion and high packet loss rate, while increasing the quality of user perception.

The QoE of online videos is affected not only by network parameters, but also by several video factors, which can vary from the video characteristics, like bitrate, codec type, and the length of the Group of Pictures (GoP), to the video content, such as the degree of details and motion intensity [4]. Thus, an adaptive redundancy control mechanism must be implemented to control the video quality level in dynamic and high error rates wireless systems (e.g., MANETs, FANETs, or VANETs). Since different videos have different motion and complexity levels, an adaptive redundancy control mechanism should protect differently frames of videos with high level of motion intensity than those with low levels. To address the aforementioned traits, an Unequal Error Protection (UEP) scheme is required to assure that the most important information will be better protected and will result in better QoE.

Adaptive protection mechanisms are required to protect the most important data, enhancing the video transmission and providing both video quality and low network overhead. To accomplish that, Forward Error Correction (FEC) techniques have been used successfully in real-time video transmission services [5]. FEC enables a more robust video transmission by sending redundant data along with the original data set. In case of a data loss incident, it is possible to reconstruct the original set through the redundant information [6]. Therefore, an adaptable cross-layer FEC-based mechanism combining UEP and QoE is required to reduce the amount of redundant information and increase the human perception. This is possible because UEP QoE allows adjusting the amount of redundancy according to the relevance of the content from the human perception, giving more weight to the most important video data.

This paper describes a novel cross-layer Adaptive Video-aware FEC and Fuzzy Logic based mechanism (ViewFECz) to improve the resilience of online video transmissions with

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both UEP and QoE-awareness. Although existing video-aware FEC-based mechanisms are effective to transmit videos with acceptable quality, they consume an unnecessary amount of additional bandwidth to send redundant and QoE-unaware information. ViewFECz uses fuzzy logic to dynamically configure itself to different video, human, and network conditions as a way to improve the video delivery. This technique has been used for a variety of purposes related to video applications. However, to the best of our knowledge, there is no proposal of a mechanism that uses fuzzy logic to handle abstract concepts, such as low, median, and high levels of motion intensity for QoE assurance in dynamic wireless networks. Another novelty is the use of the fuzzification process to control information about several video characteristics to determine the degree of membership of each video to a specific motion intensity. In doing that, it is possible to assign an optimal amount of redundant data. This means that only the more sensitive/QoE video content will carry an adjustable amount of redundant data, therefore ensuring a good video quality and downsizing the resources usage. The proposed solution was assessed using real video sequences and objective QoE metrics.

The remainder of this paper is structured as follows. The related work is shown in Section II. Section III describes ViewFECz and its evaluation is presented in Section IV. Conclusions and future work are summarized in Section V.

II. Related Work

Several techniques have been proposed to improve the quality of video transmissions over wireless networks. One of them relies in the definition of a dynamic FEC block length, which is adapted according to the number of continuous losses and average packet loss rate to improve video transmissions [7]. This solution is heavily based on network parameters and does not use QoE/video characteristics, such as frame type, GoP size, and motion activity levels in the adaptation scheme.

The Adaptive Cross-Layer FEC (ACFEC) uses a packet-level error correction scheme [8]. It verifies, at the MAC layer, when a loss occurs and a failure counter is increased. The information held by this counter determines the amount of FEC recovery packets. However, this approach does not assess the network overhead, which is very important to determine the efficiency of the solution. Moreover, it does not consider the video characteristics, which have a direct influence on how the video is resilient to packet loss and user experience level.

Another FEC mechanism uses retransmission-based adaptive source-channel rate control [9] to track in real-time the decoder buffer occupancy and channel state, to find the best redundancy amount. Although the authors claim that there has been an improvement in the QoE for end-users, this approach does not use actual QoE metrics. Instead of that, it relies on the prediction of QoE level through packet loss information. Additionally, it does not measure the network overhead that has been introduced in the system for the FEC scheme.

The Cross-Layer Mapping Unequal Error Protection (CLM-UEP) assigns a different level of redundancy according to the frame type of the video sequences and the packet loss rate [10]. Moreover, this mechanism has an adaptive mapping algorithm to direct the video data and redundant packets to the suitable Access Category (AC) queues. This operation also takes into consideration the frame type and the packet loss rate, as well as the AC queue occupancy to avoid congestion-induced packet losses. The major drawback of this mechanism is the lack of use of important video characteristics, such as levels of motion activity and position of the frames within the GoP. As evidenced before, this information plays a substantial role to define the best amount of redundancy, allowing the system to save important network resources [11].

III. Adaptive video-aware fuzzy logic mechanism

Considering the open issues aforementioned, especially the lack of QoE video-aware proposals that include a comprehensive amount of video characteristics jointly with the network state, this study describes a novel cross-layer adaptive Video-aware FEC and Fuzzy Logic based mechanism (ViewFECz). The main goal is to adapt and improve the transmission of online videos in dynamic and high error rate wireless networks. This solution is an enhancement of our previous work [12] and the main improvements are described next.

First of all, an exploratory analysis using hierarchical clustering was performed to conceive a knowledge database about the relation between video characteristics and their impact on video quality, further details can be found in [12]. By combining this knowledge database and human experience about the intrinsic video as well as network characteristics, it was possible to define a number of fuzzy rules and sets. As depicted in Figure 1, this is our offline process and needs to be executed only once. After that, this information can be introduced to the fuzzy inference engine, which will use it in the real-time decision making process. The offline process is important because it allows a fast and more accurate real-time execution, since few variables need to be handled.

Another improvement in ViewFECz is the use of the network state as input to the adaptive scheme. This new parameter is used together with the previous information provided by the mechanism, namely GoP length, frame size, type, and relative position, to set a suitable amount of redundancy. At the end, an enhanced UEP technique is used to provide the capability to add just the amount of redundancy needed to improve the video quality. A detailed description of these procedures is below.

One of the main features of our solution is a more comprehensive and dynamically adaptive scheme to assign the redundancy amount. This mechanism is based on fuzzy logic and is able to consider a large number of video and network details, and even so, it is fast enough to work in real-time schemes as expected in dynamic wireless systems, such as MANETs. Fuzzy logic puts up a simple approach to reach definitive conclusions relying on imprecise, ambiguous, or vague information. It uses linguistic variables, such as small, big, slow, and fast. By themselves, these terms may be imprecise nevertheless, they can be very explanatory of what must actually happen in a given situation. For example, if the video quality is not good and it is getting worst, our proposal should add more QoE-sensitive redundant information to increase the video quality.

A very important step in using fuzzy logic is to define the rules, sets, and membership functions. Fuzzy rules must describe how the system works. Fuzzy sets are series of elements that can have some grade of membership, unlike classical sets, in which an element either belongs or does

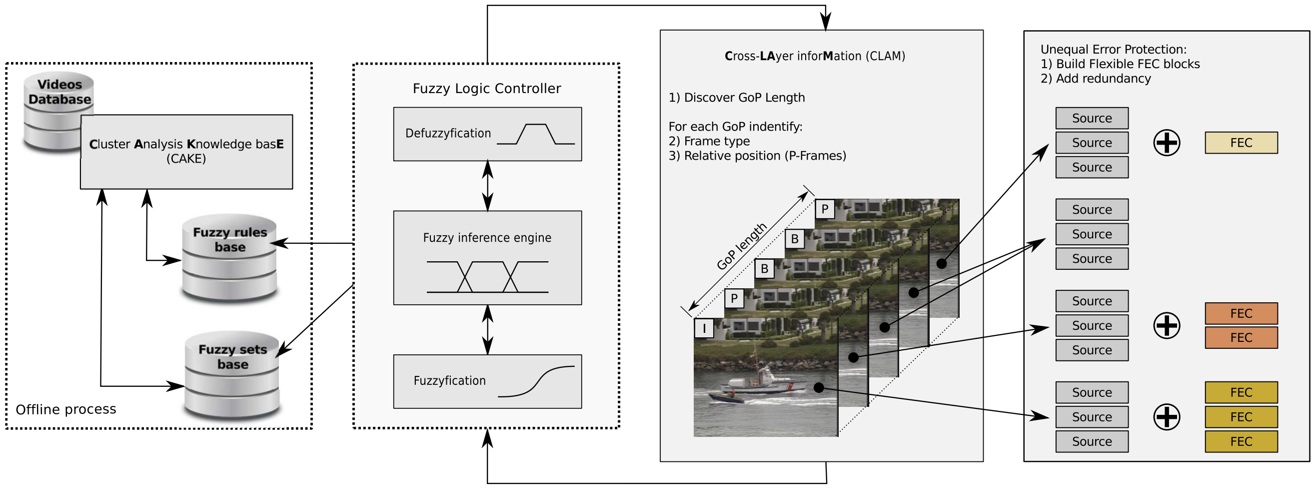

Fig. 1. ViewFECz mechanism

not belong to the set. Membership functions represent the significance of each element in the fuzzy set.

An exploratory analysis technique defines part of the fuzzy rules and sets, namely hierarchical clustering with Euclidean distance. This is a statistical method of partitioning data into groups that are as homogeneous as possible. Several videos were broken down into I-, P-, and B-Frames. Each of them was clustered together according their sizes. In other words, the frames were divided by their type and there is no distinction of which video sequence a particular frame came from. Based on the linkage distance between the clusters, the I-frame data was divided into two clusters "small" and "large". On the other hand, the P- and B-frame data were divided into three clusters, namely "small", "median", and "large".

Once the sets are defined, it is necessary to set up the membership functions. It is a complex and problem-dependent task to find an optimal solution to choose the membership functions. With that in mind, it is preferable to use piecewise linear functions (formed by straight-line sections), because they are simple and more efficient with respect to computability and resource requirements. The graphical representation of our membership functions can be found in Figure 2.

To classify each video according to the motion activity intensity and complexity levels, another type of exploratory analysis was done. This also uses hierarchical clustering with Euclidean distance and the same video sequences used before. However, differently from the previous analysis, the video sequences were not broken down, allowing the entire video to be analysed as one. Again, I-, P-, and B-Frames sizes were used and clustered into three distinct groups, i.e. "low", "median", and "high" motion. Using this information, a number of rules were derived through the combination of human knowledge of video characteristics with network simulator experiments.

Once the intensity of the motion activity was defined, it is necessary to delineate the packet loss rate set. The main idea with this activity is to quantify the packet loss rate against the video quality in terms of QoE. This means that a loss rate of 10% can be characterized as low to us, but it could be unacceptable to other types of applications, for example a voice over IP (VoIP) call. To define this set, a number of network simulations with different packet loss rates and a broad collection of video sequences were carried out. On

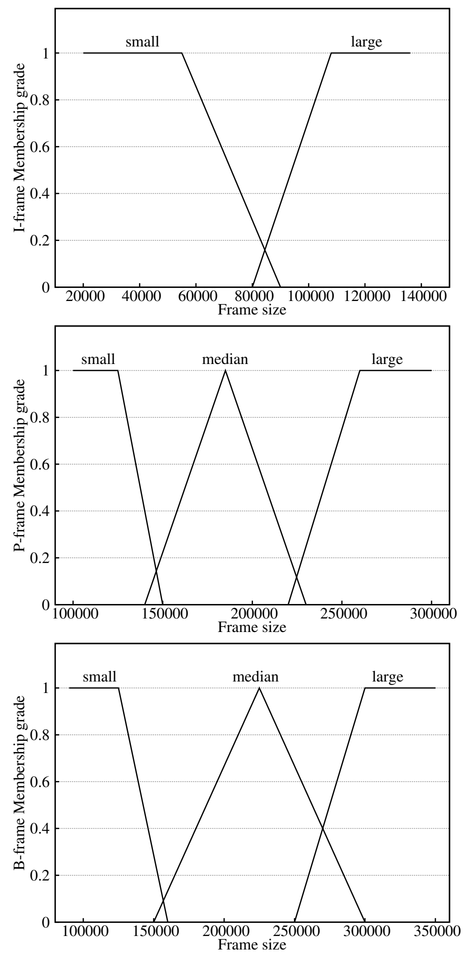

Fig. 2. Frame size membership function

average, the video quality was considered good when the network losses were between 0% and 10%. A reasonable quality was perceived between 5% and 20%, and over 15% the quality decreases rapidly, becoming unacceptable. Based on that, three categories were defined, namely "low", "median", and "high", as shown in Figure 3.

A further step is to define the redundancy amount set. This set will aim to establish the output value for the redundancy

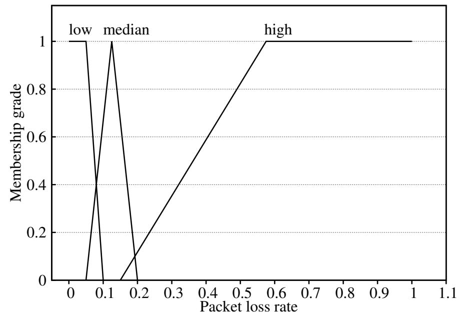

Fig. 3. Packet loss membership function

amount. Several experiments were conducted and with the aid of human knowledge in the field to specify what would be a “small”, “median”, and “large” amount of redundancy. Figure 4 displays the graphical representation of the membership function found.

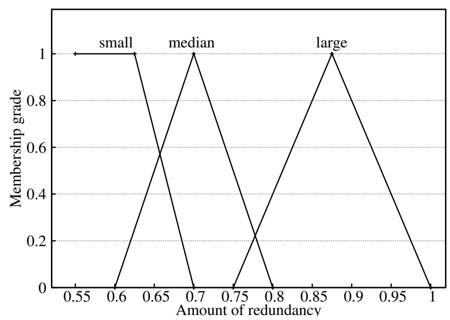

Fig. 4. Redundancy amount membership function

Finally, the fuzzy rules can be described. The activity is straightforward, if a video sequence has low levels of motion activity and the packet loss rate is also low, then the redundancy amount added by the ViewFECz is also low. The same idea holds true for “median” and “high” characteristics as depicted in Figure 5.

```
RuleBlock* block = new RuleBlock();

block->addRule(new MamdaniRule("
 if Motion is LOW_INTENSITY and
    PacketLossRate is LOW
      then RedundancyAmount is SMALL", engine));

block->addRule(new MamdaniRule("
 if Motion is MEDIAN_INTENSITY and
    PacketLossRate is MEDIAN
      then RedundancyAmount is MEDIAN", engine));

block->addRule(new MamdaniRule("
 if Motion is HIGH_INTENSITY and
    PacketLossRate is HIGH
      then RedundancyAmount is LARGE", engine));
```

Fig. 5. Packet loss x redundancy amount rules

After the conception of the rules and sets they need to be loaded in the Fuzzy Logic Controller (FLC). This activity has to be performed only once, during the system setup period (bootstrap). Once the FLC is defined, it will calculate the degree of membership of each input information, resulting in a precise amount of redundancy on the fly.

IV. Performance Evaluation and Results

The ViewFECz mechanism aims to improve the perceived video quality without adding unnecessary network overhead. The evaluation experiments were carried out by using the Network Simulator 3 (NS-3). The evaluation scenario is composed of a grid of nine static nodes (3x3), 90 meters apart from each other. Constant Bit Rate (CBR) background traffic of 800 kbps was added. A set of ten different video sequences with Common Intermediate Format (CIF) size (352x288), GoP length of 19:2, and H.264 codec were used. The selected video sequences cover different distortions and content, being representative of regular viewing material. Additionally, these sequences include colour and luminance stress, still and cut scenes, as well as motion energy and spatial detail. The chosen error concealment method was Frame-Copy, that is, the lost frames will be replaced by the last good one received. The Packet Loss Rate (PLR) ranged from 0% to 40% in increments of 5% as expected in dynamic wireless systems.

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) with a video-aware FEC-based approach (where both I- and P-Frames are equally protected) with a pre-defined amount of redundancy set to 65% (video-aware FEC). This redundancy amount showed, in average, a good tradeoff between video quality and network overhead under the different PLR; (3) our previous work with a simple adaptive UEP (ViewFEC) [12]; (4), with an implementation of the Cross-Layer Mapping Unequal Error Protection (CLM-UEP) [10]. Finally, (5) adopts our novel ViewFECz mechanism.

The set up simulation is composed of 9 different PLRs (ranging from 0% to 40%), 10 video sequences, and 5 cases. Each of them was simulated 30 times to get a confidence interval of 95%. Two main QoE metrics were used to perform the video quality assessment, namely Structural Similarity Metric (SSIM) and Video Quality Metric (VQM). These metrics were adopted because they are the most widely used [13]. The quality assessment was conducted using Evalvid [14] and MSU Tool [15].

Figure 6 shows the average SSIM for all the video sequences when the system is configured with all approaches. For SSIM, values closer to one indicate a better video quality. As expected, there is a decline in the video quality as the PLR increases. In the first case (without FEC), there is a sharp decline in the video quality after 15% of PLR. On the other hand, for videos transmitted with the aid of FEC-based mechanisms (cases 2 to 5), the sharp decline is only noticeable after 20% of PLR. This is evidenced because of the natural video resiliency to a certain amount of packet loss. In other words, videos tend to be resistant to certain loss, but after a certain limit, the quality decreases rapidly. The increase in the standard deviation values between PLR 10% and 20% can be explained by the different video characteristics. For example, video sequences with low spatial and temporal complexities are more resilient to loss, and achieve better results in the QoE-aware assessment. On opposite, flows with high spatial and temporal complexities, had poor results. The standard deviation obtained indicates that the values of the QoE assessment are more distant from each other.

Almost the same pattern is found in the VQM values as presented in Figure 7, where, videos with better quality score close to zero. To better represent the values found, the first

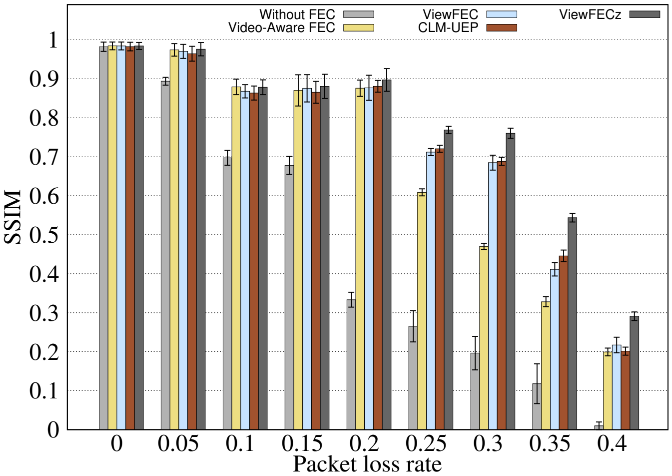

Fig. 6. SSIM QoE for all scenarios

case (without FEC) was not included in this graph because it has a large difference form the other cases, up to 19.6. It is possible to notice that, with a packet loss rate of 5% and 10%, the VQM values are also fairly close to each other. This is not as evident as in the SSIM metric because VQM tends to be more rigid when there are video impairments, and yields poor results to videos with fewer flaws. For the same reason, the standard deviation of this metric has a tendency to be higher than the SSIM metric.

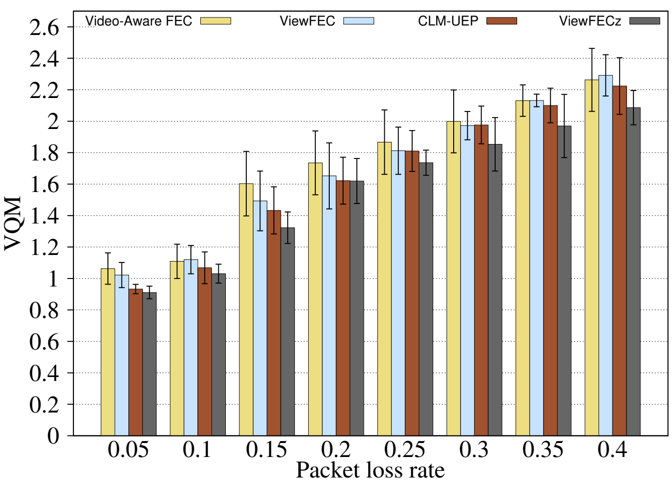

Fig. 7. VQM QoE for all scenarios

The comparison of ViewFECz and the related work [10] can be found in Figure 8. It is shown the percentage of QoE improvement and the amount of redundancy added by our mechanism compared to CLM-UEP for all PLRs. In the case of QoE improvement, for example, with 30% of loss, the ViewFECz was able to achieve a video quality 10.44% better than CLM-UEP. As evidenced in our experiments, with up to 20% of PLR, both mechanisms had the same video quality. In these cases, the ViewFECz achieved a small improvement, between 0.16% and 1.85% only. The real advantage of ViewFECz is noticeable when the loss is greater than 20%. At 25% of PLR our improvement reached 6.67% and rapidly increased to 44.48% of better video quality when the PLR was 40%. The viewFECz performs better in highly error-prone networks, such as those found in wide coverage areas with wireless video cameras for security, environment control, and natural disaster sites.

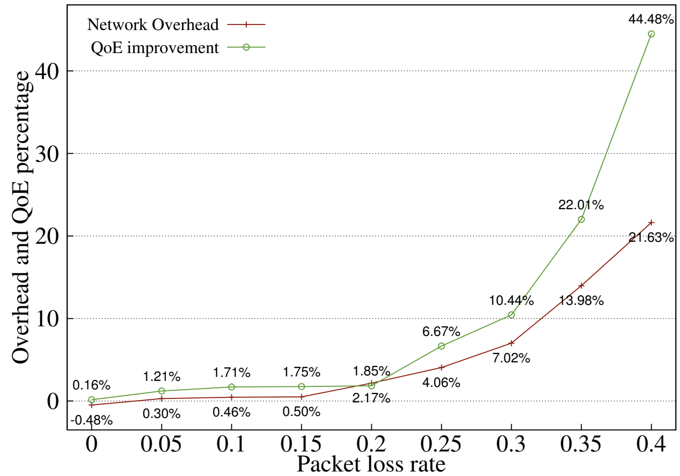

Fig. 8. ViewFECz in comparison to CLM-UEP

Figure 8 also shows the difference in the amount of redundancy added by ViewFECz in comparison to CLM-UEP. A positive percentage means that ViewFECz added more redundancy than CLM-UEP. Up to a PLR of 15% both mechanisms had almost the same network overhead, thereafter ViewFECz begins to increase the redundancy. This happens because our mechanism was developed to improve the video quality over error-prone networks. This means that it will have to better protect the most important video data, producing more overhead. For example, when the PLR is 20%, our mechanism added 2.15% more redundancy than CLM-UEP. The highest difference can be noticed at 40%, when ViewFECz added 21.63% more redundancy. The increased redundancy is a response of our mechanism to better improve the video quality. The QoE assessment, also shown in the figure, demonstrates that it provides a good tradeoff between video quality and network overhead.

A comparative analysis can also be done with Figure 8. It is clear that up to 20% of PLR both mechanisms had similar results, but ViewFECz added a slightly higher redundancy and had a modest improvement in the video quality. After this threshold, our mechanism starts adding a larger amount of redundancy aiming to improve the quality of video. As a result, it was possible to have videos transmitted with more than 44% better quality adding approximately 21% more redundancy in comparison to CLM-UEP. The advantage of our mechanism is that it uses the video motion activity to define the redundancy amount, thus videos that have higher motion activity receive more redundancy and we are able to delivery better video quality (with a better user perception).

The two QoE metrics that were employed demonstrated that the ViewFECz mechanism was able to improve the video quality in different scenarios, especially for high PLRs. Another important goal of ViewFECz is to use the least possible redundancy amount to maintain a low overhead. This is a very important issue considering the limited wireless channel resources, the uneven bandwidth distribution and the interference caused by concurrent transmissions present in wireless transmission. The network overhead, in our experiments, is given by summing the size of all video frames transmitted. In doing that, it is possible to measure the specific amount of redundancy added by each mechanism. The video-aware FEC and ViewFEC mechanisms do not adjust the redundancy amount according to the state of the network; hence, in all packet loss rates they have the same FEC overhead, which was 65.10% and 38.90%, respectively, as shown in Figure 9. The same figure shows results for ViewFECz and CLM-UEP, which take into account the state of the network. ViewFECz added an overhead between 2.71% and 90.27%, and CLM-UEP between 2.73% and 74.22%.

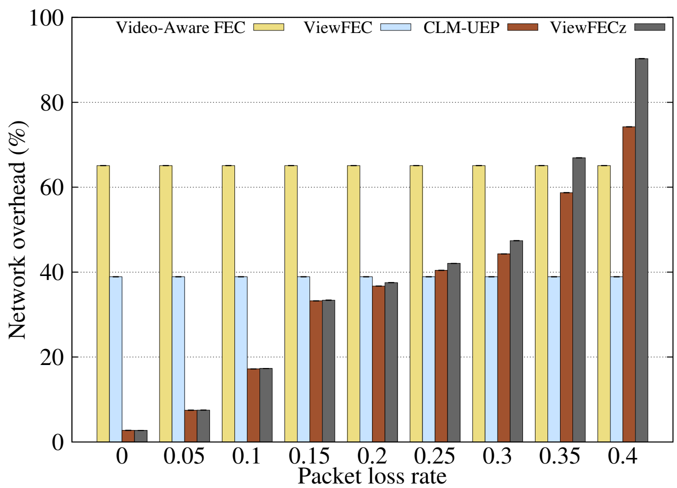

Fig. 9. Network overhead for all scenarios

V. Conclusion and Future Works

Due to the growth of video transmissions over wireless networks, an adequate mechanism to increase the resiliency to packet loss with QoE support is essential. The ViewFECz provides the capability to enhance video transmissions in dynamic networks, and consequently, improving the video quality, without adding unnecessary network overhead and maximizing the QoE. This approach leads to a better usage of the already scarce wireless resources for video delivery. A set of experiments was performed to show the impact and benefit of ViewFECz in enhancing video transmissions, especially in dynamic and high error rates wireless networks. It is possible because the redundancy scheme is also based on key human visual system and video characteristics, namely, GoP size, frame type, and position, as well as the levels of motion activity in each video sequence. Besides that, the network state, i.e. packet loss rate, was also considered.

The experiment results exhibit that our mechanism (ViewFECz) was able to improve the video quality without adding an unnecessary amount of redundancy when PLR is up to 20%. On the other hand, when the PLR is over 20%, there is an increase in the network overhead, which was not more than 22%, however, we successfully achieved over 44% of improvement in video quality. It provides a good tradeoff between network overhead and quality improvement and was only possible because our mechanism adds a certain amount of redundancy considering the video characteristics and the network state. As a future work, a generic data input is going to be developed allowing the use of video sequences with arbitrary size and codec type. Additionally, other scenario configurations will be adopted, e.g., multi-hop networks, as well as subjective QoE assessment will be done.

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