International Journal of Computer Applications (0975 – 8887)
Volume 65– No.6, March 2013

Neural Network-based Video Quality via Adaptive FEC in Wireless Environment

Ghaida A. AL-Suhail
Computer Engineering Department, University of Basrah Basrah ,Iraq

Sarah A. Subber
Computer Engineering Department, University of Basrah Basrah ,Iraq

ABSTRACT
Artificial Neural Network (ANN) has proven capability in wireless communications. Therefore it has been used for a variety of purposes and in different ways. This proposal strives to address QoS of video streaming for the cellular clients in Universal Mobile Telecommunication System (UMTS) through adaptive FEC based on ANN. The model aims to present the idea of configure and recover the corrupted packets in the video flow with a suitable Forward Error Correction (FEC) code addressed by the ANN. The adaptation of the FEC scheme is based on predefined probability equations which are derived from the data loss rates related to the recovery rates at the clients. The client-side is responsible to relay information to the BS by the feedback channel via RTT of TCPFriendly Rate Control Protocol (TFRCP). For each video, the neural network will be trained on the precise data. The simulation results show that a video quality can be adaptable to the tuned optimal FEC codes from ANN via the packet loss probability of the wireless feedback environment.

Keywords
Quality of Service, FEC, UMTS, ANN.

1. INTRODUCTION
The Quality of Service (QoS) in wireless mobile networks refers to the capability of a network to provide better service and good transmission quality. The 3G like UMTS network, are recently developed for high data rate transmission, and inculcate various multimedia services for voice, data and video that provide a good QoS. However, the major challenges in cellular networks that may decline the QoS ranks are the varying rate channel characteristics, bandwidth allocation, fault tolerance levels and handoff in which packets are likely to be lost. In video transmission even a small amount of network packet loss can have a dramatic impact on video streaming. So, the protection of the compressed video stream from channel errors is very important. Automatic Retransmission reQuest (ARQ) and Forward Error Correction (FEC) are the two most commonly-used error control schemes [1]. Recent literature has revealed that employing FEC on corrupted packets yields better bandwidth utilization and lower delay than with ARQ, and thus FEC has been extensively used to increase error resilience in multimedia communications [2]. Since the FEC redundancy requires extra bandwidth, intelligent FEC redundancy adjustment has been an important issue in preventing unnecessary trade-off or network congestion caused by too much redundancy in previous FEC studies. The packet size control in [3] is one of the adaptation ways of solving the burst packet error in video streaming that decreases the bandwidth up to 52% from the traditional FEC. In [4] the author proposed a dynamic switching FEC between 4 different FEC techniques to adapt the varying network conditions. Also using the Artificial Neural Network (ANN) has proven capability in wireless communications in building wireless intelligent systems. The basic purpose of applying neural networks is to change from the lengthy analysis and design cycles required to develop high performance systems to very short product-development times. The rapidly evolving field of neural-network applications in wireless communication has witnessed several excellent contributions [5][6] different problems have been successfully attacked new methodologies have been introduced and significant progress has been made in this dynamic area. The study in [7] presents a multilayer perceptron (MLP) based media access control protocol (MAC) to secure a CSMA-based wireless sensor network against the denial-of-service attacks launched by adversaries . In [8] a learning model based on Adaptive Neural Fuzzy Inference System (ANFIS) was proposed, the model takes into account the Radio Link control (RLC) loss models to predict the video quality in terms of the Mean Opinion Score (MOS) over UMTS network. This proposal strives to address QoS of video streaming over UMTS network based on ANN. The ANN will be learned to obtain the appropriate FEC code for good desired QoS at the mobile client. The process is based entirely on channel feedback: Packet loss probabilities of the TFRCP acknowledge. The rest of this paper is organized as follows. Section II provides system model. Our proposed analytical models of (ANN_AFEC) control system video transmission, System senior, System settings, Results and performance comparison are presented in Section III. Finally, Section IV summarizes the conclusion and outlines of some future works.

2. SYSTEM MODEL
In this paper, we consider a video flow in a point-to-point wireless network which is simply composed of one Base Station (BS) in UMTS and a single user end. This last wireless link is connected to a wired Internet via this base station [9]. Moreover, UDP/RTP/IP will be the transmission protocols underplaying TCP-Friendly. Within this scenario, we can outline the key network assumptions:

1. Video traffic transmitted is assumed to be MPEG-4.

2. The wired link is defined with no congestion raised at the Base Station (BS) node due to other cross-traffics. By this, we mean that there is no loss that occurs on video packets between the server and BS.

3. Only the effect of wireless link is taken into account to describe the end-to-end packet loss rate (P) caused by the wireless channel errors during transmission. Thus the packet loss is assumed to be random and stationary.

4. Packet size (S) for all connections of one application is the same, unless otherwise stated.

5. The streaming rate is denoted by (T), where throughput is considered to be TCP-Friendly flow.

6. The Gilbert Elliot error model is considered to describe the burst error pattern and to be the wireless virtual channel. The model was derived for wireless video transmission in our previous work in [10].

Thus the normalized available bandwidth of a TFRC video session with respect to TCP packet size can be expressed as [11]

$$T = \frac{S}{t_{RTT}\sqrt{\frac{2P}{3}} + t_{RTO}(3\sqrt{\frac{3P}{8}})P(1+32)} \quad (1)$$

where S is the TCP packet size [byte], P stands for the average packet loss probability, i.e. loss event rate due to only the channel bit errors and there is no buffer overflow effect at the base station. RTT t is the round-trip time [sec], and RTO is the TCP retransmit time out value [sec].

Encoded video is transmitted as a repeating sequence of Group-Of-Picture (GOP) [11], with the start of each GOP formed by an I-picture. An I-picture is the basis for prediction of all other pictures in the GOP (usually 12 to 15 pictures in all) and, hence, its loss has drastic consequences for all other pictures. P-pictures also form the basis for predictions but are not essential for the reconstruction of other pictures within the GOP (as other I- or P- anchor pictures retained in a decoded buffer can be applied). Lastly, the third type of picture, the bipredictive B-picture, has no predictive value. Since equation (1) provides an expression for T as TFRC throughput, the GOP rate can be written as;

$$G = \frac{T/S}{(S_I + S_{IF}) + N_P(S_P + S_{PF}) + N_B(S_B + S_{BF})} \quad (2)$$

where N_P represents the number of P frame in a GOP and N_B is the number of B frame in a GOP.

The total PFR by Wu et al.'s, technique is given by [11];

$$PFR = G.P_{SI}.(1 + \frac{P_{SP} - P_{SP}{}^{N_P+1}}{1 - P_{SP}} + N_{BP}.P_{SB}.(\frac{P_{SP} - P_{SP}{}^{N_P+1}}{1 - P_{SP}} + P_{SI}.P_{SP}{}^{N_P})) \quad (3)$$

where P_{SI}, P_{SP} and P_{SB} are the probabilities of success transmission of I, P, or B frame.

To improve video quality it has been assumed that P_{SI}, P_{SP} and P_{SB} is the probability that the sender transmits N packets over two models of Gilbert channel and the receiver correctly receives K packets. Also, it has been indicated in [12] that the models probability can be expressed as

$$P_{avg} = P_0\pi_0 + P_1\pi_1 \quad (4)$$

where P_{avg} is the average packet loss rate product by the Gilbert Eliot model (GE), π_1 and π_0 study state probability being in good state and bad state.

3. PROPOSED APPROCH

3.1 Maxmin optimization

To achieve our goal in this paper, Fig. 1 depicts the video flow model under consideration. It involves the artificial neural network which is employed to control FEC Code at the video application layer. The Maxmin decision theory is the first method utilizes to find the optimum FEC for the network. An obvious requirement of a good PFR search is that, makes the interval of uncertainly as big as possible, thus on maximizing, PFR can be written as;

$$PFR_{\max-GEM} = \max_{0\le FEC\le i}(PFR_{GEM\_FEC}(FEC, P)) \quad (5)$$

The PFR_{GEM_FEC} is the PFR for GEM for i FEC Sets code.

3.2 Neural Network Adaptive FEC (ANN_AFEC)

An ANN is a massively parallel distributed processor that stores experimental knowledge; this knowledge is acquired by a learning process and is stored in the form of parameters of the ANN. The ANN consists of a number of neurons arranged in a particular fashion. Each node in a neural network can have more than one input and each of it has a weight associated to it. The functional block diagram of a neuron is shown in Fig.1(b). ANN can be trained by two forms of learning: supervised and unsupervised learning. Supervised learning needs an external teacher, which directs each output unit towards a desired response for an input signal. It aims at minimizing the difference between the actual and the desired output by adjusting the weights with this calculated difference. Most used is the Least Square Method (LSM) for error convergence in supervised learning. Unsupervised learning does not require an external teacher and is based only upon local information. It is also refer as a self-organization.

In our application neural network is trained to pick the suitable FEC from the input feedback average Packet loss probability (P). The client-side is responsible to relay information to the BS by the feedback channel via RTT of TCP-Friendly Rate Control Protocol (TFRCP). For each video, the neural network will be trained on the precise data. Fig.1 (b) shows the state diagram of the ANN-AFEC with four neuron inputs and one output. The state diagram can be shown in a matrix form as;

Input matrix $PFR_{FEC(i)}(P)$ (6)

Output vector $FEC = \sum_{r=0}^{i} w_r PFR_{FEC(r)}(P)$

i=0, 1, 2, 3 (7)

Where $PFR_{FEC(i)}$ is the PFR with set of FEC codes, P is packet loss probability, ρ is the packet correlation, w_r is the input weight and finally; the index i denoted the FEC weight.

Since Least Mean Square (LMS) algorithm is widely used in supervised learning systems to provide the minimum of error between the desired and computed unit values. In our proposed model, the Back propagation algorithm based on LMS will be used.

Based on the key preliminaries required to predict FEC codes based on neural network adaptive FEC over UMTS, one can compute the $PFR_{\max-GEM}$ by equations 1 to 5. to find the optimal FEC.

3.3 System Settings

Table 1 describes network characteristic of many typical network connections [2][11][13] which we used in our simulation. Encoded video is transmitted as a repeating sequence of GOP (N_P, N_{BP}) pattern, where N_P =3 and N_{BP} =2. The P00 , P11 and P0 are set at 0.96, 0.94 and 0.001 respectively. The packet error rate is set between 0.001 to 0.1 with 0.001 intervals [2]. Also, the packet correlation is set between the values of 0.1 to 0.9 with 0.1 intervals. In [11] the author summarized the FEC weights in three groups, in which the I frames always receive more FEC packets than the P frames. Similarly, the P frames always receive more FEC than the B frames. Thus FEC weights were ranged from 1 to 10 with 1 interval as Table 2 shows.

Table 1.(a) System Settings; (b) FEC Weights

(a)

Parameter	value	
t_{RTT}	168ms	
t_{RTO}	$t_{RTT} \times 4$	
N_P	3	
N_{BP}	2	
S_I	24.64KB	25 packet
S_P	7.25KB	8 packet
S_B	2.45KB	3 packet

(b)

code	FEC weight	S_{IF}	S_{PF}	S_{BF}
1	Noun	0	0	0
2	Small	1	1	0
3	Medium	4	2	0
4	Large	8	4	1

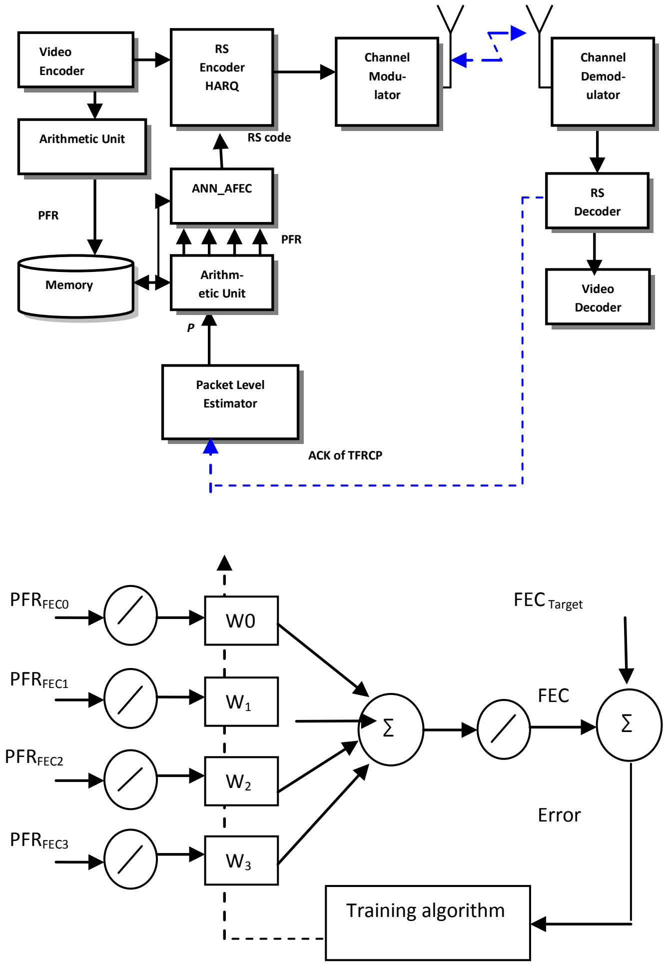

Fig. 1 (a) Video Streaming Architecture in Which Neural Network is Considered to Control FEC Code, (b) NN-AFEC State Diagram

3.4 Performance Evaluation

This section describes the PFR of an MPEG4 Video streaming over wireless channel using the GEM video model as an error model. The performance evaluation is carried out by considering the parameters in Table 1 for the fact that maximum frame rate allowed over Internet is 30fps. The results are conducted using Matlab package.

Chart in Fig. 2, shows the $PFR_{\max-GEM}$ defined in equation 5. Regardless of the first value in chart table, the chart in the figure clearly indicates better performance, in which solve the fluctuation in PFR in different FEC weights. In the previous study [10] we shows that, video PFR improve better performance over a light weight FEC (1, 1, 0) when small probability packet loss is set and less PFR performance at high weight FEC. For Probability more than the threshold value the medium weight FEC improves the performance.

The $PFR_{\max-GEM}$ is a control stage where FEC weight were chosen depending on the network situation. In GEM the packet loss probability is finding to be the effective factor one can clearly see that P=3% is the threshold value for FEC weights.

Fig. 4 depicts the fitting Plot for desired FEC and the Trained FEC. The ANN_AFEC is design as a two layer feed forward network with ten hidden neuron and a liner output neuron. The network is designed with four present inputs and one desired output as shown in Fig. 5. The network will be trained for 4 [sec] with the Back propagation training progresses and evaluate its performance using LMS. The figure plots the neural network output and the average packet loss, and also shows a small amount of error in training. However, it is difficult to distinguish the best linear fit line from the perfect fit line because the fit is so good. By test and experiment increasing the hiding neuron gets more efficiency (i.e. less error) than the design one. Therefore one can conclude that, the GEM_ANN_AFEC improve the performance of the network by assigning appropriate FEC for video transmission over the UMTS channel.

4. CONCLUSON

In this paper, we have proposed an effective scheme called ANN_AFEC designed for video flow to improve the QoS in the presence of Gilbert Elliot channel model over UMTS environment. The Maxmin optimization is use to fined the maximum PFR between a set of FEC codes, where the target vector of FEC code was computed. ANN is use to fit the FEC code for the next transmission, depending on channel feedback. The neural network obtained a very small attenuation as shown in Fig. 4 and almost an idle fitting and this performance will introduce a very good improvement in resultant PFR at the client end. In contrary, neural network is very complexity where it does require normalization process, learning process and labelled training data. For further work, this proposed scheme can be implemented using NS-2.

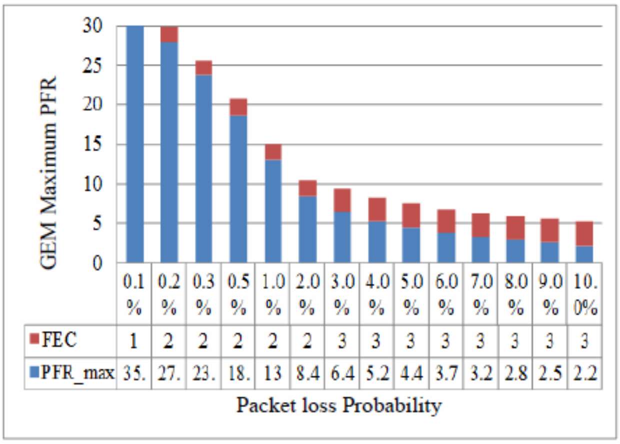

Fig. 3. Maximum PFR vs. the Probability of Loss and Packet Correlation

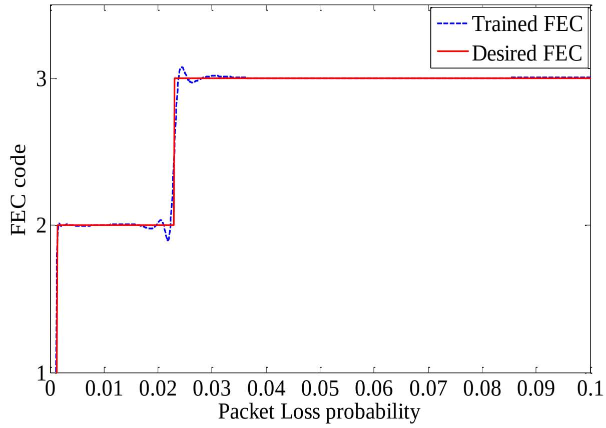

Fig. 4 The Desired FEC and the Trained FEC vs. Packet Loss Probability for GEM Video Model

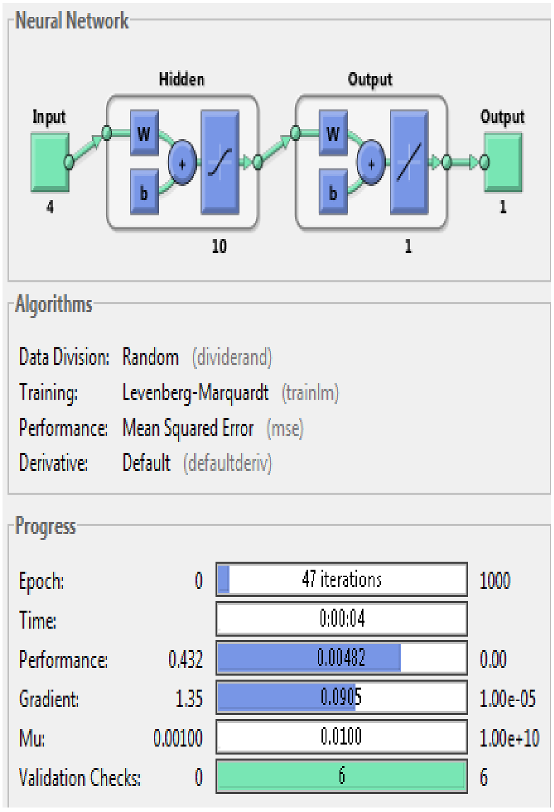

Fig.5 A Block Diagram and Performance of ANN-AFEC for GEM Video Model

5. REFRENCES

[1] Oskar Eriksson. 2011. "Error Control in Wireless Sensor Networks A Process Control Perspective," Examensarbete 30 hp.

[2] M. WU, H. Radha. 2005. "Network Embedded FEC (NEF) Performance Over Multi-hop Wireless Channels with Memory," Conf. on Information Sciences and Systems, The John Hopkins University.

[3] C. Shih. 2010. "Adaptive Forward Error Correction Combined with Packet Size Control for Wireless Video," Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 2010 Sixth International Conference.

[4] C. Lamoriniere, A. Nafaa, and Liam Murphy. 2010 "Dynamic Switching Between Adaptive FEC Protocols For Reliable Multi-Source Streaming," Communications Technology (NICT).

[5] A. Patnaik & D. Anagnostou. 2004 "Applications of Neural Networks in Wireless Communications," IEEE Antennas and Pmpagalion Magazine,, vol. 46, no. 3.

[6] L. Khoukhi. 2009. "Toward Neural network solution of multimedia support in mobile Ad hoc network," Journal of network, vol. 4, no. 2.

[7] R. Kulkarni, Senior , G. Venayagamoorthy.2009 "Neural Network Based Secure Media Access Control Protocol for Wireless Sensor Networks," Proceedings of International Joint Conference on Neural Networks, Atlanta, Georgia, USA, pp. 14–19.

[8] A. Khan. 2010."Impact of RLC losses on quality prediction for H.264 video over UMTS networks," Multimedia and Expo (ICME), IEEE International Conference.

[9] M. Chen and A. Zakhor.2004. "Rate Control for Streaming Video over Wireless," IEEE INFOCOM.

[10] S. Subber and G. Al suhail. 2012. "Robust Network FEC-Embedded Video Transision over Error-Prone Wireless Channels," International Journal of Wireless & Mobile Networks (IJWMN) vol. 4, no. 3.

[11] H. Wu. 2003 "A Model for MPEG with Forward Error Correction and TCP-Friendly Bandwidth," NOSSDAV'03.

[12] G. Haßlinger and O. Hohlfeld. 2008. "The Gilbert-Elliott Model for Packet Loss in Real Time Services on the Internet," Darmstadt University of Technology, Germany.

[13] G. Al Suhail and R. Kennedy. 2009. "Modelling of Adaptive Wireless Link or MPEG-4 Video transport in UMTS Network," Inter Conf. Signal processing and communication system ICSPCS, USA.