Final Report of Major Research Project

Titled

VIDEO STREAMING IN 3G WIRELESS NETWORK FOR TELEMEDICINE APPLICATION

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Submitted by

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PROGRESS THROUGH KNOWLEDGE

ज्ञान-विज्ञान विमुक्तये

PROFORMA

1.	UGC Approval Letter No. & Date	41-190/2012 (SR) dated 16-07-2012
2.	Title of the Project	Video Streaming in 3G Wireless Network for Telemedicine Application
3.	Name & Address of The Principal Investigator	Dr. Dhananjay Kumar Professor Department of Information Technology Anna University, MIT Campus Chennai-600044
4.	Department & University where the project has been undertaken	Department of Information Technology Anna University, MIT Campus Chennai-600044
5.	Tenure of the Project	24-12-2012 to 31-12-2015
6.	Total Grant Allocated	Rs.7,70,116
7.	Objectives of the Project	Develop a system to support adaptive video streaming in 3G/4G wireless network for telemedicine application
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PRINCIPAL INVESTIGATOR

ABSTRACT

The smooth and reliable video streaming over HTTP through 3G/4G wireless network for telemedicine application is challenging as available bit rate in the internet changes due to sharing of network resources and time varying nature of wireless channels. The present popular technique Dynamic Adaptive Streaming over HTTP (DASH) provides solution up to some extent to stored video, but the effective adaptive streaming of a live video remains a challenge in a high fluctuating bit rate environment. In this project, some intelligent algorithms based on client server model are designed, developed, and implemented in real-time internet environment with last mile connectivity as wireless. In buffer filling based algorithm, the client system analyses the incoming bit rate on the fly and periodically sends report to server which in turns adapts the outgoing stream as per the feedback. The system was implemented and tested in real-time in CDMA 1xEVDO Rev-A network using internet dongle. The use of maxima minima concept and an RMS approximation which tries to estimate the bit rate pattern in real-time provides an improvement of 37.53% in average PSNR (Peak Signal to Noise Ratio) and 5.7% increase in mean SSIM (Structural Similarity Index) over traditional buffer filling algorithm on a live video stream. The second method is based on ARIMA Based Bit Rate Adaptation (ABBA) model, where the receiver/client side estimate network traffic based on the incoming packet bit rate to predict the subsequent future link capacity in order to notify the sender/server. Based on the response from the receiver the server adapt its outgoing stream as per forecasted link data rate, and hence eliminate the degradation of video due to channel throughput variations. The ABBA algorithm was implemented on IP over 4G wireless network and the streaming quality was evaluated on several full reference metrics of video quality. The test result outperformed an existing buffer based approach and also a fuzzy based adaptation algorithm. The ABBA algorithm exhibited an average increase of 9% in SSIM than a buffer based method. In third method, a machine learning based approach is implemented, where State Action Reward State Action (SARSA) Based Quality Adaptation algorithm using Softmax Policy (SBQA-SP) identifies the current state (Throughput), action (Streaming quality) and reward (current video quality) at client to determine the future state and action of the system. The ITU-T G.1070 recommendation (parametric) model is embedded in the SBQA-SP to implement adaptation process. The system was implemented on the top of HTTP in a typical internet environment using 4G wireless network and the streaming quality is analyzed using several full reference video metrics. The test results outperformed the existing Q-Learning based video quality adaptation (QBQA) algorithm. An average improvement of 2 % in SSIM index over the QBQA approach was observed for the live stream.

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LIST OF ABBREVIATIONS

3G	Third generation of wireless mobile telecommunications technology
3GPP	3rd Generation Partnership Project
3-SSIM	Three-component Structural Similarity Measurement
4G	Fourth generation of broadband cellular network technology
ABBA	Auto Regressive Integrated Moving Average (ARIMA) Based Bit Rate Adaptation
AIC	Akaike Information Criterion
A-PSNR	Aligned-Peak Signal to Noise Ratio
AR	Auto Regressive
ARIMA	Auto Regressive Integrated Moving Average
AVC	Advanced Video Coding
BSR	Buffer Switching Rate
CDMA	Code Division Multiple Access
CIF	Common Intermediate Format
CPU	Central Processing Unit
DASH	Dynamic Adaptive Streaming over HTTP
EVDO	Evolution-Data Optimized
FPS	Frames Per Second
FR	Full Reference
GB	Gigabyte
HAS	HTTP based Adaptive Streaming
HD	High Definition
HDR	Heuristic Decision Rate Adaptation
HEVC	High Efficiency Video Coding
HTTP	Hypertext Transfer Protocol
IEC	International Electrotechnical Commission
ISO	International Organization for Standardization
ITU-T	International Telecommunication Union-Telecommunication
JPCAP	Java network packet capture
JVT	Joint Video Team
LTE	Long-Term Evolution
Mbps	Megabits per second
MPEG	Moving Picture Experts Group
MSE	Mean Square Error
MS-SSIM	Multi Scale- Structural Similarity Index
NR	No-Reference
OSMF	Open Source Media Framework
PSNR	Peak Signal to Noise Ratio
QBQA	Q-Learning Based Quality Adaptation

QCIF	Quarter Common Intermediate Format
QoE	Quality of Experience
QVGA	Quarter Video Graphics Array
RAM	Random-access memory
RL	Reinforcement Learning
RMS	Root Mean Square
RTCP	RTP Control Protocol
RTP	Real-time Transport Protocol
SARSA	State Action Reward State Action
SBQA-GP	SBQA using ε-Greedy Policy
SBQA-SP	State Action Reward State Action (SARSA) Based Quality Adaptation using Softmax Policy
SQCIF	Sub Quarter Common Intermediate Format
SSIM	Structural Similarity index
SSIM	Structural Similarity Measurement
SVC	Scalable Video Coding
TCP	Transmission Control Protocol
TDD	Time Division Duplex
UDP	User Datagram Protocol
URL	Uniform Resource Locator
VCEG	Video Coding Experts Group
VGA	Video Graphics Array
VLC	VideoLAN Client
VLCJ	VideoLAN Client Java framework
VNI	Cisco Visual Networking Index
VQM	Video Quality Metric

CHAPTER – 1

INTRODUCTION

1.1 MOTIVATION

The latest development in wireless mobile communications along with developments in pervasive and wearable technologies is supposed to have a direct influence on future healthcare systems. The live video streaming enables the predictive analytics of data in motion for real-time decisions allowing medical expert to capture and analyze data. Many times when doctors are on move or out of station, their expertise are needed at hospital for critical health care. In this situation, a medical video streaming becomes the most demanding application as it provide visual and other data to deliver expert opinion. Further, the medical video communication techniques for tele-medical applications have requirements of high fidelity. In order to keep diagnostic accuracy high, the wireless network along with the wired internet must support high quality live streaming considering best effort service model of the internet protocol.

1.2 OBJECTIVES OF THE PROJECT

The main objective of this project is to develop a system working on existing 3G/4G wireless cellular network that permits a medical expert not only get connected to health center but also watch, monitor, and advice to an live critical medical activity. The live medical video as well as stored image/video need to be transferred over wireless mobile network to the expert irrespective of his location and movement. However the available bandwidth for any user using dongles in 3G networks varies with time and location. An intelligent system at source capture and encode video such that a best quality video is delivered at the receiver. This necessitates the dynamically adjusting the video parameters as per the available network bandwidth in a feed-back loop.

The prototype system need to permit medical expert to communicate simultaneously with other experts at hospital premises through using laptops with 3G/4G dongle. The existing popular streaming video codec e.g., H.264 is to be incorporated in the system to support adaptive streaming considering the prevailing network bandwidth.

1.3 ADAPTIVE VIDEO STREAMING OVER INTERNET

The adaptive video streaming over Hypertext Transfer Protocol (HTTP) in internet has become very popular today as HTTP is a widely used web technology, and it does not require any specific technique below it to support streaming. In this aspect to ensure interoperability, MPEG and 3GPP has developed a new standard called *Dynamic Adaptive Streaming over HTTP* (DASH) [1]. In DASH, each video is fragmented and stored with different quality parameters (e.g., resolution, frame rate etc.). The adaptation process at the client request the server to stream the appropriate quality segment based on the prevailing network bandwidth [2]. The present heuristic algorithms fail to respond an abrupt change in network bandwidth, which leads to freeze in the video at play, thereby degrading the quality of experience [3]. Furthermore, a new approach is needed in DASH in implementing live streaming.

In live streaming, even a highly adaptive buffer management technique which involves client monitoring the upper and lower threshold of the play out buffer, may not produce good result as content rate depends on live capturing mechanism at the source. This clearly justify the need for the on the fly Scalable Video Coding (SVC) mechanism. The SVC can support frame by frame adaptation provided the system permits to switch the video layers dynamically [4].

The user data traffic in wireless mobile network has been increasing rapidly across the globe. As per the Cisco Visual Networking Index [5], the 4G wireless network will have the highest stake (40.5 %) of total mobile connections worldwide, and 75% of the global mobile data traffic will be video by 2020. Such remarkable progress is fueled by the video streaming service over internet by YouTube, Netflix, etc. The ever increasing number of smart phones with internet access over 4G wireless network is another reason for the tremendous increase in streaming video traffic.

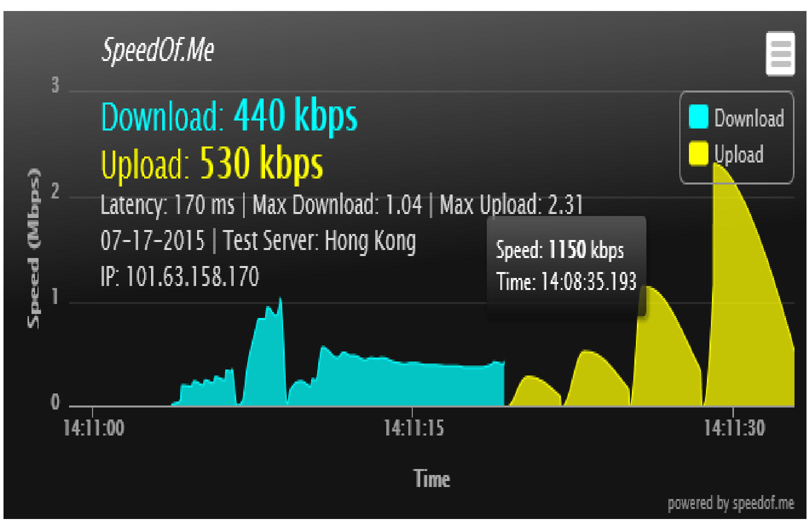
The ultimate objective of all streaming services is to deliver seamless content to the end user in real-time, though it poses a huge challenge due to large fluctuating bandwidth in the network. To provide user the seamless multimedia service with maximum achievable Quality of Experience (QoE), the media content in particular video need to be adaptive to match the available bit rate in the network. The traditional streaming method based on progressive download fails to cope up with dynamic network traffic [6] thereby degrading the media quality.

The streaming techniques [7] are classified into three major classes: i. Traditional Real-time Transport Protocol (RTP)/ RTP Control Protocol (RTCP), ii. Progressive streaming (HTTP/TCP), and iii. Adaptive streaming (HTTP/TCP, UDP). The HTTP based Adaptive Streaming (HAS) has exhibited resilience to the internet traffic and hence widely used as DASH in the present systems. The use of DASH in entertainment based utilities, where the stored videos are being streamed to the client, requires segment based information and pre-defined streaming parameters to facilitate ease in deciding the upcoming bandwidth changes. However in live streaming where the video content is created and encoded only when the systems connect in real time over the network, the adaptability of DASH to intimate the sender about the link bandwidth becomes an encumbrance for targeting an improvement in the perceived quality of video by the user [8].

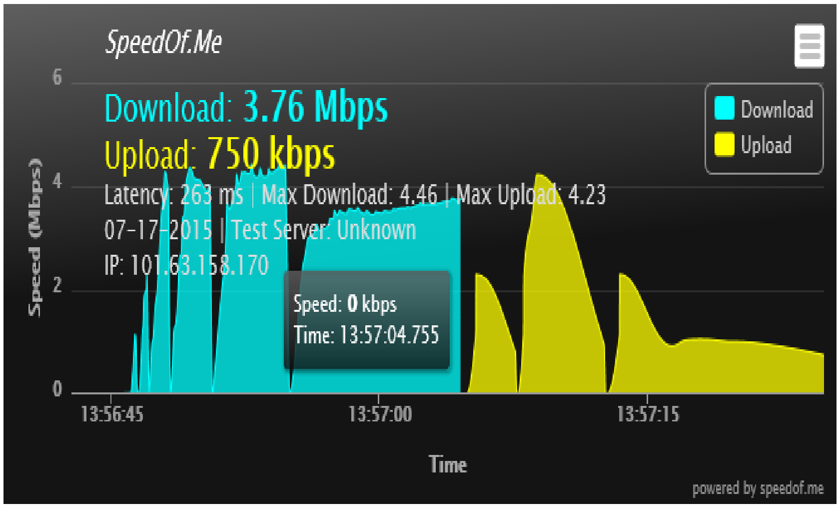
1.4 CASE STUDY OF AVAILABLE DATA RATES

1.4.1 Bit Rate in 3G and 4G Wireless Networks

One of the main motivating reasons to develop an adaptive SVC based video streaming system here arises from the study of available bit rate in existing wireless internet dongles (3G and 4G). Although the system supporting these devices have been designed to meet the standard specification, in practice there is a lot of gap between what is mentioned by the service provider and the actual resource available to the end customer due to various reasons. Fig.1.1 shows the observation of a 3G dongle employing *CDMA 1xEVDO Rev-A* technique and a 4G dongle based on *LTE TDD Category-3* system. The measured data rate not only varies from locations to locations but also fluctuate in time.



(a) Data rate observed on a *Reliance Netconnect+* (CDMA 1xEVDO Rev-A) 3G dongle



(b) Data rate observed on an *Airtel 4G Mobile Hotspot* (LTE TDD Category 3) dongle

Figure 1.1. Download and upload bit rate observed on wireless internet dongles at work place in a given time

The bit rate observation was repeated on existing 4G wireless network, the uplink and downlink data rate on the Airtel 4G LTE-TDD Hotspot [9] system was monitored in same laboratory environment (Fig. 1.2). Although these wireless systems are designed to support up to 100 Mbps in high mobility access, the actual capacity at user premises not only fall much below the specified values, but also fluctuate over time. Clearly there is a high incentive in developing a video streaming system which can adapt to this network operating environment while offering best performance and hence video quality to the end user.

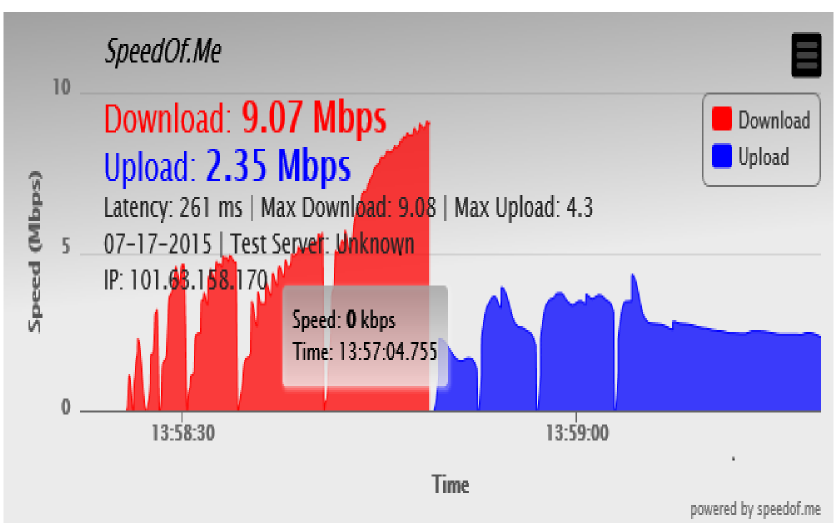


Figure 1.2. Bitrate observed during streaming of live videos using Airtel 4G dongle

1.5 SYSTEM ARCHITECTURE

The traditional approach of link bandwidth estimation at the client/server used to send a ping packet to the server/client and calculate the bandwidth with reference to the time taken by the packet to return. This approach is not accurate as there are many factors like instant congestion that can delay the arrival rate of a ping packet. Thus the best approach to this problem will be to estimate the link capacity at the receiver/client by analyzing incoming bit stream on the fly. The incoming bit rate can be sampled periodically to send a feedback message to the server to carry out any remedial action on the outgoing stream such that the end user enjoys a best quality of content all the time. Fig.1.3 shows a schematic of proposed system where client applies a predefine algorithm to estimate the incoming bit rate and report to the server. The action in the loop needs to be fast enough to respond the real-time requirement of the video communication.

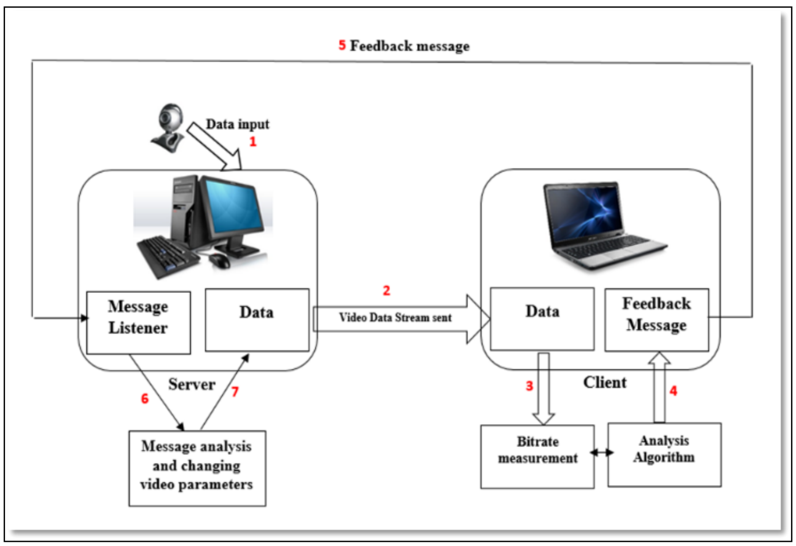


Figure 1.3. The schematic of an adaptive video streaming

1.5.1 The Client Server Approach

The proposed system architecture consists of two modules at the server side (Fig.1.4) to acquire and stream live/stored video and three modules at the client side (Fig.1.5) to receive, analyze, and play video. The server captures the live video stream through a high-definition (HD) video camera connected locally. The video stream is then encoded by a H.264 based codec. The live video stream is then streamed to the client, which is connected through a 3G wireless network. After receiving *N* frames (say *N*=100) of video steam the client starts playing it and simultaneously it also estimates the incoming bit rate of the video. A pattern estimate algorithm is applied on the receiving bit rate to pass feedback to the sender. If the pattern suggests that the bitrates are either high or low and point towards a degradation, a response message is sent to the server to make suitable changes to the video stream.

1.5.2 Server side modules

The server continuously monitors the client feedback and decides the parametric values of outgoing video stream. The server side implementation contains two basic modules:

- The first module uses the *vlcj* framework including H.264 codec to capture and stream the video data continuously to the client through the *http* port.
- The second module listens to the feedback messages received from the client for adjusting parameters (e.g., resolution, frame rate) of the video stream.

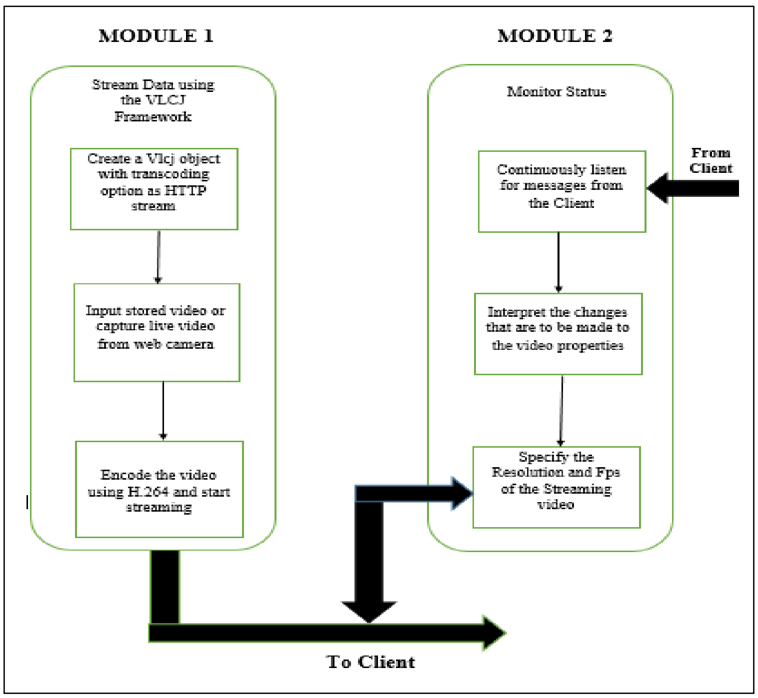


Figure 1.4. Server side modular flow diagram

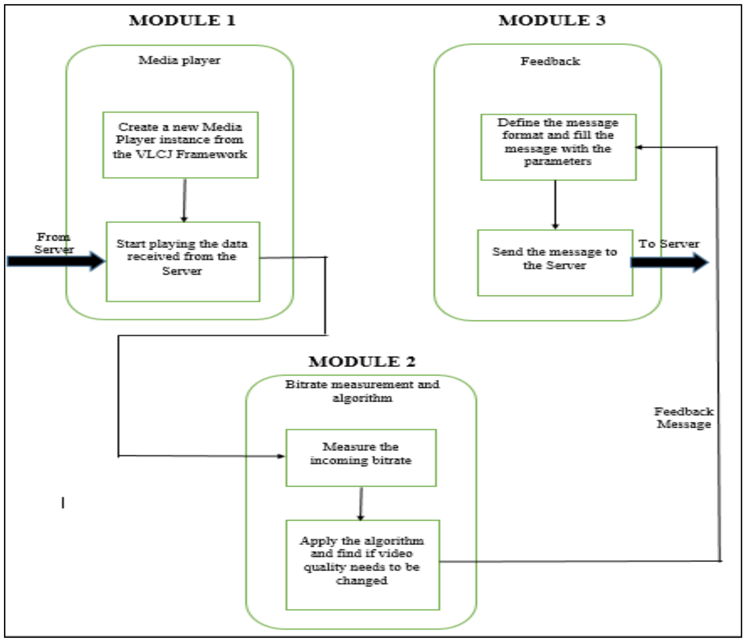


Figure 1.5. Client side modular flow diagram

1.5.3 Client side modules

The client analyses the incoming bit stream periodically to find out the pattern of variation of receiving bit rate. The client side contains three modules:

- The first module uses the *vlcj* framework to play the stream of data received from the server.
- The client system is responsible for estimating the bit rate from the received video and applying the algorithm to analyse the pattern of bit rate which is performed by module 2.
- The main job of the third module is to pack the feedback messages in agreed format and send to the server.

1.6 THE ITU-T RECOMMENDATION

The system performance needs to be evaluated using standard parameters and procedures. As per the ITU-T recommendation (J.247) on “objective perceptual video quality measurement”, the *full reference measurement* method can be used when the original reference video signal is obtainable at the receiver (decoding point), and hence it is suitable to test an individual equipment or a chain in the laboratory [10]. The assessment techniques are applied on video in QCIF, CIF, and VGA format for testing. As listed in Table 1.1, these test factors provide a very low to high quality input to assess the system under test conditions. The proposed system intends to utilize these parameters with corresponding standard values for validation and testing.

Table 1.1. Test Factors as per the ITU-T J.247

S.No.	Parameters	Values
1	Transmission	Errors with packet loss
2	Frame rate	5 fps to 30 fps
3	Video Codec	H.264/AVC (MPEG-4 part 10), VC-1, Windows Media 9, Real Video (RV 10), MPEG-4 Part 2
4	Video Resolution: QCIF, CIF, and VGA	QCIF: 16 - 320 Kbps CIF: 64 - 2000 Kbps VGA:128 - 4000 Kbps
5	Temporal errors (pausing with skipping)	Maximum of 2 seconds

1.7 ORGANIZATION OF THE REPORT

The chapters of the report are organized as follows:

- The Chapter 1 provides the general overview and case study about the adaptive video streaming technology and overall system architecture.
- The Chapter 2 starts with adaptive video streaming over http by pattern matching and proceeds to explain about the Buffer Filling Algorithm and its implementation details, finally ends with results and discussion.
- The Chapter 3 provides an overview of the Auto Regressive Integrated Moving Average (ARIMA) Based Bit Rate Adaptation (ABBA). Then the system modelling and algorithm development with implementation details are given. The section ends with results and discussion.
- The Chapter 4 starts with the details of machine learning approaches used for the adaptive video streaming and proposed system architecture. Then the machine learning algorithms used in the project is explained with implementation details. The chapter ends with results and discussion.
- The Chapter 5 provides the overall conclusion of the project along with the details of further improvements and the scope for extension of project in future.

CHAPTER – 2

ADAPTIVE VIDEO STREAMING OVER IP BY PATTERN MATCHING

2.1 EXISTING APPROACH

Understanding the theory behind the bit rate adaptation and analysing factors like video segment scheduling, selection of bit rate, and bandwidth assessment with respect to the performance of commercially available solutions like SmoothStreaming, Akamai HD, Netflix, and Adobe OSMF could be rewarding [11]. Further, a proper modelling of the main process i.e., automatic switching of video stream in the system adopted by these commercial (video streaming) service provider, helps in improving system design as it involves analysis of feed-back control loops [6].

In HTTP based Adaptive Streaming (HAS), the switching of video i.e., bit-rate stream at client dictates the main parameter of quality of experience (QoE) [12]. The analytical model/framework of QoE needs to include the probability of play out buffer getting drained, running playback time, average quality of video etc. The client system can estimate buffer level over time, and there is need to maintain balance between the stability of buffer and quality of play out video [13]. Hence, any adaptation on layer switching in SVC needs to accommodate the probability of buffer underflow of the receiver [4].

There has been considerable interest in MPEG – DASH by many researchers. A proper mapping between DASH layers and SVC layers can not only help in estimating needed bitrates, but also enhancing the video throughput with reduced overhead of the HTTP messages [2]. It could be further rewarding to work on scheduling and resource allocation through a cross-layer approach which include DASH and radio layer. The DASH can be implemented to support streaming to hand-held mobile devices through multiple wireless network interfaces, but not only the energy efficiency but also the cost of service becomes an important factor [14-15]. Some researchers [16] have argued that when HAS occupies a considerable fraction of the total internet traffic and multiple HAS clients start competing at a network resources, it will result in problem of its fair share of bandwidth and a possible solution could be a probe and adapt policy. Furthermore, a HAS client can apply machine learning of reinforcement type to adapts its behaviour leading to the optimization of its quality of experience [17].

2.2 ALGORITHM DEVELOPMENT

The proposed algorithm analyses periodically the sampled data (bit rate) and provide solution to the fluctuating available resource in the network. The fluctuating received bit rate is categorized it into any one of the predefined pattern (Fig.2.1). The algorithm at receive includes local maxima and minima of sampled data before it concludes the pattern as either of (i) Progressive, (ii) Stabilized, (iii) Fluctuating, and (iv) Degraded. Sometimes it may declare status as non-monotonic where it needs to find the RMS value. The algorithm at server side decodes the received message from the client and decides the video stream accordingly. The server also considers switching time as a metric in deciding change in outgoing stream. Any error in estimating pattern at client will result in non-remedial action by the server.

2.2.1 Client side algorithm

1) Read the bitrates and store in a buffer.
2) Find local maximum points and store it in an array "$\boldsymbol{L_{max}}$"
   i) Read bitrates in pairs of 3 *// i.e., v_1, v_2, v_3*
   ii) If $v_1 < v_2 > v_3$, add v_2 to L_{max} array *// set max.*
   iii) Continue the process for the all the frames received.
3) Find local minimum points and store it in an array "$\boldsymbol{L_{min}}$"
   i) Read bitrates in pairs of 3 *// i.e., v_1, v_2, v_3*
   ii) If $v_1 > v_2 < v_3$, add v_2 to L_{min} array *// set min.*
   iii) Continue the process for the N ($N=100$) frames received.
4) Max = Analyse (L_{max}) *// Call function to get α, β, γ*
5) Min = Analyse (L_{min})
   i) If $max = \beta$ and $min = \beta$, set status as **Progressive**.
   ii) Else if $max = \beta$ and $min = \alpha$, set status as **Stabilized**.
   iii) Else if $max = \alpha$ and $min = \beta$, set status as **Fluctuated**
   iv) Else if $max = \alpha$ and $min = \alpha$, set status as **degraded**.
   v) If $max = \gamma$ or $min = \gamma$, Set status as **non-monotonic** and call **Find_rms(Bitrates)**

2.2.2 Analyse (Bitrates)

1) Find start
2) Find end
3) Locate median
4) If (start, median, end) are monotonically increasing, Return β
5) Else if (start, median, end) are monotonically decreasing, Return α
6) If (start, median and end) are neither monotonically increasing nor decreasing, return γ

The system analyses the bitrates and categorize them into four different patterns (Fig.2.1) and adapts the ongoing session corresponding to each case. Case 1 represents a progressive type where the network bit rate will increase in time. After some fluctuation the bit may tend to become stable (Case 2). There may be a case when pattern of change in bit rate may diverge (Case 3). If the received bit rate continues to fall, it represents a serious problem in maintaining quality of service (Case 4).

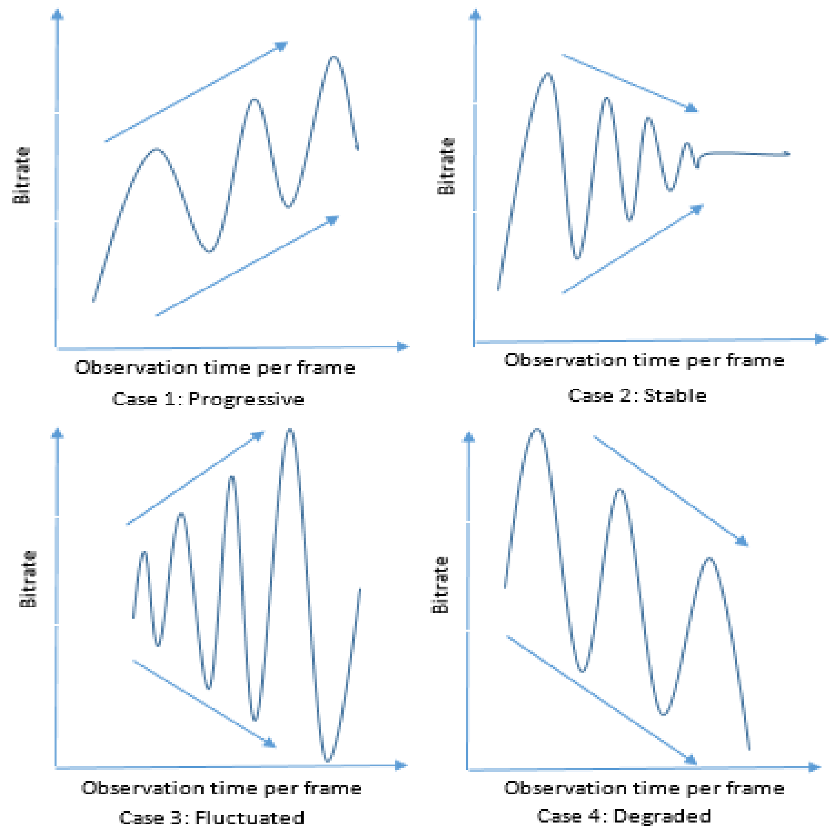


Figure 2.1. Different bitrate patterns

If the system is unable to resolve into any of these categories, it will resort to a root-mean-square (RMS) value.

2.2.3 Find_rms (Bitrate)

1) Find the RMS value of the bitrates.

$$x_{rms} = \sqrt{\tfrac{1}{n}\left(x_1^2 + x_2^2 + \dots + x_n^2\right)} \tag{2.1}$$

2) Split the N different (N = 100) bitrates into M parts (M = 3)
3) Repeat the first step to find the RMS values of the each (three) parts. Let them be rms_1, rms_2, and rms_3
4) Find the difference between the total RMS value and the RMS values of the parts.
   i) Compute $Diff_1 = RMS - rms_1$
   ii) Compute $Diff_2 = RMS - rms_2$
   iii) Compute $Diff_3 = RMS - rms_3$
5) If ($Diff_1 <= Diff_2 <= Diff_3$), then return 1
6) Else if ($Diff_1 >= Diff_2 >= Diff_3$), then return 0
7) Else return 2

2.2.4 Server side algorithm

// *S* = Spatial Resolution, *T* = Temporal Resolution
$S = \{S_1, S_2, S_3, S_4\}$, $T = \{T_1, T_2, T_3, T_4, T_5\}$

1) Initially set the resolution in QCIF at default value, T_d
2) Repeat
   i) Receive status from the client
   ii) If status = Good
      a) Continue with same configuration.
   iii) Else if status = Stable
      b) Experiment with increased temporal resolution.
   iv) Else if status = Fluctuated
      c) Find_Switching_time (bitrate).
   v) Else if status = Degraded
      d) Reduce both spatial and temporal resolution.
   vi) Else if status is non-monotonic
      e) Wait for next feedback to make change
3) Until connection is terminated

2.2.5 Find_Switching_Time (Bitrate)

1) Quality switching time $T_{switch} = TQ_{k+1} - TQ_k$ //*where TQ_{k+1} is the time-instant at the end of k^{th} quality request processed and TQ_k is the current time instant serving previous quality request.*
2) Start a timer when each quality switch is encountered to find the time needed to switch from one quality level to another.
3) Wait till next feedback from the client.
4) If (T_{switch} > Fluctuation_time)
   i) Do not alter the quality and wait till next feedback from the client
5) Else, Alter the quality as per the current request.

2.2.6 Buffer Filling Algorithm

The buffer filling algorithm was implemented independently here which is based on traditional adaptive stream control method. The system at the client monitors the lower and upper threshold of the play out buffer and submits the report to the server. If the buffer reaches the upper threshold it ask for slowing down the stream rate but if the arriving contents approaches the lower threshold it signals the server to speed up the transfer rate. The server reduces or increases the stream bit rate by changing the video frame resolution and/or dropping frames accordingly.

2.3 IMPLIMENTATION ENVIRONMENT

We considered four standard video resolutions namely SQCIF, QCIF, CIF, and QVGA to be adopted dynamically by the server based on client feed-back. The four temporal resolutions (in fps) was: 10, 15, 25, 30, and 35; whereas the default frame and also initial set-up was fixed at 30 fps. The server system was programmed using our proposed algorithm to choose any of these combinations (spatial and temporal) to match the available outgoing bit rate in the communication channel. The wireless internet connectivity was established by a dongle, *Reliance Netconnect+* [18] which works on CDMA 1x RTT & CDMA 1xEVDO Rev A. As per the specification mentioned by the service provider it is intended to provide a download speed up to 3.1 Mbps and up to 1.8 Mbps in uplink, but according to a real-time test conducted with the help of an online tool by *SpeedOf.Me* [19] the average uplink speed was found to be 0.54 Mbps and the average downlink rate was 0.45 Mbps during the experimentation. The internet bit rate fluctuation in *Reliance Netconnect+* in real-time during test and measurement provided us the perfect platform to asses our proposed algorithms. The client and server were implemented on Dell Inspiron N5010 desktop computer separately which is configured with *Intel® Core™* i7-3770 CPU@3.4 GHz processor and 8 GB RAM. The *Window7 Professional* 32-bit operating system was installed to run the client/server program. The streaming operation was carried over http with UDP protocol.

2.3.1 Video Streaming and Bitrate Estimation in Java Framework

The VLCJ in a Java framework is used here as an instance of a native VLC media player. It helped in a higher level framework while hiding a lot of the intricacies of working with VLC libraries. Since VLC supports many video/audio formats under *libavcodec* it play back the H.264 streamed video. JPCAP provide a packet capture function (library) for the network applications in Java specifically to analyse the real time network data. It is used here at client side to estimate the bitrate of the incoming video and to store it in a buffer (array) where the client program continuously evaluate it for further action.

2.3.2 Parameters Used to Evaluate the System Performance

Since the targeted application here is a high quality video communication services including tele-medical video, the full reference (FR) methods were used to evaluate the system performance. Moreover FR metrics usually provide the most accurate result. The two commonly used FR parameters are: Peak Signal to Noise Ratio (PSNR) and Structural Similarity (SSIM) index. One of the main aims of implementation here is that the system response to the changing network resource should result in higher PSNR and SSIM provided the communication link is maintainable.

2.3.2.1 Peak Signal to Noise Ratio (PSNR)

The PSNR reveals the overall degradation of processed video signals and it can be computed on luminance value (ITU-T recommendation [20]) and usually it is represented on a logarithmic scale as:

$$PSNR = 20\log_{10}\left(\frac{Max}{\sqrt{MSE(m)}}\right) \tag{2.2}$$

where $Max = 2^{\text{no. of bit/sample}} - 1$ and for 8-bit per luminance value it is 255. The *MSE(m)* is the mean square error which is the difference between the reference video and degraded video in the m^{th} frame, and it is computed as:

$$MSE(m) = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[Y_{out}(i,\,j,m) - Y_{in}(i,\,j,m)\right]^2 \tag{2.3}$$

The PSNR measurements were carried out on few selected decoded frame at the receiver resulting from the application of proposed adaptation algorithms. It was basically an offline process where at the end of experiment the recorded data were compared and analysed. The system was targeted to maintain an average PSNR of not less than 30 dB.

2.3.2.2 Structural Similarity (SSIM) Index

The SSIM index provides knowledge about perceived degradation due to structural deformation in an image reconstruction. In video pixels have not only the temporal dependency but also the spatial inter-pixel dependency. The spatial dependency offers details about structure of the objects in an image and hence SSIM becomes important quality evaluation parameters in video communication. The SSIM index is evaluated on three different measures, the luminance, contrast, and structure comparison which is defined by the Joint Video Team (JVT) of ISO/IEC MPEG & ITU-T VCEG as [21]:

$$l(\mathbf{x},\mathbf{y}) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \tag{2.4}$$

$$c(\mathbf{x},\mathbf{y}) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \tag{2.5}$$

$$s(\mathbf{x},\mathbf{y}) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3} \tag{2.6}$$

where μ_x is the average of x, μ_y is the average of y, σ_x^2 is the variance of x, σ_y^2 is the variance of y, σ_{xy} is the covariance of x and y. The constants C_1, C_2, and C_3 are given by $C_1 = (K_1 L)^2$, $C_2 = (K_2 L)^2$ and $C_3 = C_2 / 2$, which are to stabilize the division with weak denominator. L is the dynamic range of the pixel values given by $L = 2^{\text{no. of bit/pixel}} - 1$ and $K_1 \ll 1$ and $K_2 \ll 1$ are two scalar constants.

Based on these metrics, the SSIM is formulated as

$$SSIM(\mathbf{x},\mathbf{y}) = [l(\mathbf{x},\mathbf{y})]^{\alpha} \cdot [c(\mathbf{x},\mathbf{y})]^{\beta} \cdot [s(\mathbf{x},\mathbf{y})]^{\gamma} \qquad (2.7)$$

where α, β, and γ state the different weightage assigned to each measure.

The single scale SSIM is now formulated as [22]:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)\,(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad (2.8)$$

The aim of the proposed system was to maintain the SSIM index above 0.95. Like PSNR the SSIM too was computed offline on stored data at the end of experimentation.

2.4 RESULTS AND DISCUSSION

2.4.1 Inter-packet Arrival Delay

The variation of packet delay as a difference in end-to-end one-way delay between selected consecutive packets in a flow with any lost packets being ignored was observed during experimental set of video communication. The observed random variation in delay (Fig.2.2) is attributed to the prevailing internet traffic during test and measurement period on 3G wireless modem (dongle) used to connect with the internet. Although maximum delay requirement was not directly dealt with the proposed algorithm, the bit rate was adjusted by the server to meet the targeted quality. For the data shown in Fig.2.2 the average inter-packet delay is 69µs.

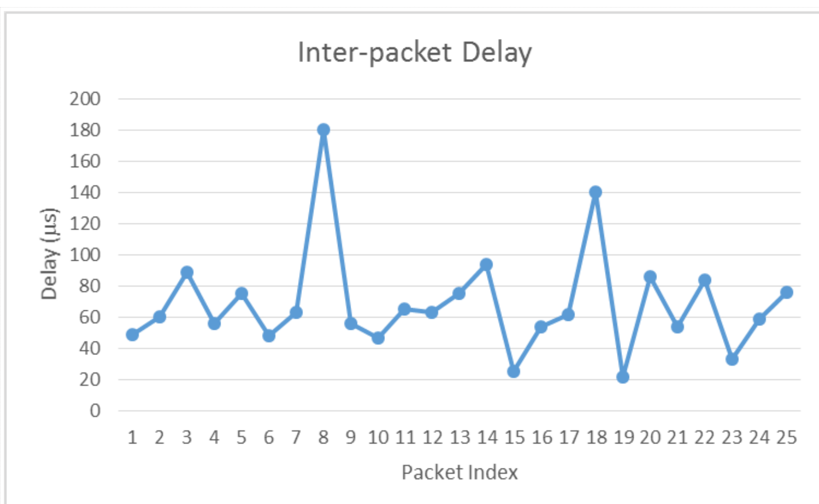


Figure 2.2. Inter-packet delay

2.4.2 PSNR Measurement

The PSNR measurement (Fig.2.3) was carried out on three approaches: (i) Without any adaptation mechanism, (ii) Buffer filling algorithm, and (iii) the proposed adaptation method. The proposed algorithm helps in achieving an average PSNR of 36.267 dB which is 37.53% higher compared to the buffer filling algorithm. Further it is much higher than the without adaptation approach. This reward of increase in PSNR is attributed to the high adaptation exhibited by the proposed method in real-time scenario which in turn permitted underlying networks to deliver packets with fewer losses.

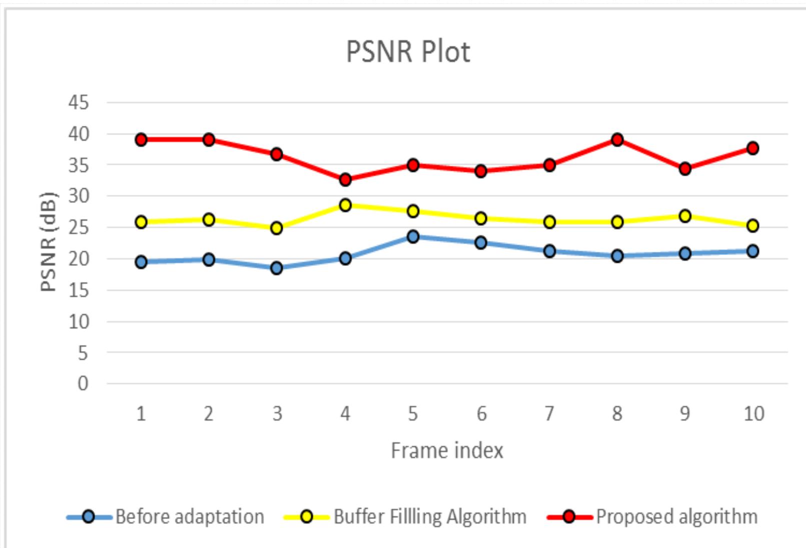


Figure 2.3. PSNR Measurements

2.4.3 SSIM Index

The SSIM index was computed in a similar way as that of PSNR on the three methods i.e., without adaptation, buffer filling algorithm, and proposed algorithm (Fig.2.4). The proposed algorithm offers 5.7% higher average SSIM value than the buffer filling algorithm and much higher than the without adaptation approach. Because of dynamic adaptation it was possible to retain and maintain the structural information thereby resulting in higher SSIM index value. Although the system designs do not include any parameter to retain the structural similarity during play out, a higher SSIM value is an additional reward of in time adaptation.

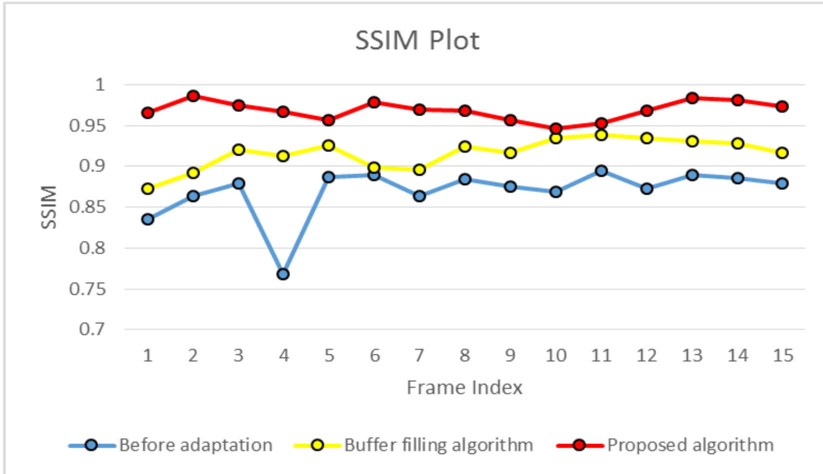


Figure 2.4. SSIM Index comparison

2.4.4 Some Selected Original and Received Decoded Frame

Fig.2.5 and Fig.2.6 show the original and received decoded frames captured during live video streaming and recorded Foreman video [23] respectively. Even a closer look at these frames does not reveal a noticeable loss in decoded video quality, which is highly desirable in high quality video communication services.

Figure 2.5. Some selected frame from live video stream: Original (above) and received (below)

Figure 2.6. Some selected frame from stored Foreman video [23]: Original (above) and received (below)

CHAPTER-3

ARIMA BASED ADAPTATION METHOD

3.1 OVERVIEW

The variations of incoming bit rates while the video is being streamed can be analogized to a time series to rigorously analyze the past observations to make forecasts about network conditions. The limitations of traditional linear regressive models need to be rectified where the seasonality of a regularly repeated pattern could be eliminated with increased focus towards accurate predictions. In this paper, a new algorithm based on a non-linear stochastic model called, Auto Regressive Integrated Moving Average (ARIMA) Based Bit Rate Adaptation (ABBA) is proposed. The ABBA algorithm is modeled on a time series consisting of sequence of sampled bit rate over a continuous time interval to analyze a successive statistical measurement that has no natural ordering for the observations. This stochastic model is used for trend analysis of the forthcoming bit rates, which decides the resolution of video to be sent from the server. The strategic decisions are based on the successive observation of sampled bit rate in a regular time interval to understand the nature of series.

To analyze the performance of the proposed ABBA algorithm, two existing approaches: i. Heuristic Decision Rate Adaptation (HDR), and ii. Buffer Switching Rate (BSR) algorithms has been formulated and developed here. The HDR [24] employs the difference in arrival time of packets and buffering time as inputs for predicting the near future using a set of decision rules whereas the BSR monitors the buffer occupancy [25] level dynamically and chooses the mode of operation based on its fill percentile using harmonic mean to effectively identify the nature of network for streaming the videos.

The ABBA, HDR, and BSR algorithm were implemented using VLC Framework in Java (VLCJ) that is completely open source and can easily be plugged into to the existing systems. The system level implementation was in adherence to the ITU-T J.247 recommendation (Table 3.1) that describes about the ‘objective perceptual multimedia video quality measurement’. The developed system were tested for delay variability ITU-Y.1540 [26] and quality of video were observed using PSNR ITU-R J.340 [27] and VQM ITU-J.149 [28] along with other standard popular video quality evaluation metrics.

Table 3.1. Test factors as per ITU guidelines

Parameter	Standard	Metrics
Frame Rate	ITU –T J.247	5 to 30 fps
Codec		H.264
Resolution		QCIF,CIF,VGA
Temporal errors		<=2 sec
Min bandwidth Required		QCIF 16 kbps to 32kbps CIF:64 kbps to 2Mbps VGA 128 kbps to 4 Mbps
Performance Metrics	ITU-R J.340	PSNR >=25
	ITU-T Y.1540	Delay Variation (Quantile and min delay difference should not be >50 ms)
	ITU-T J. 149	VQM [0-1]

3.2 SYSTEM ARCHITECTURE

3.2.1 The Client Server Model

The proposed system architecture emulates the client server model where server's job gets simplified on the expense of client's increased monitoring and analysis process. The server consists of three sub modules: i. Frame capture, ii. Streaming the video, and iii. Receiving feedback. On the other hand, the client consists of three modules: i. Decoder / Player, ii. Stream flow analysis, and iii. Receiver's feedback. The video being streamed is encoded dynamically using ITU-T H.264 [21] video codec. The live (or stored) video is streamed from the server to client through 4G wireless networks and the client scrutinizes the link bandwidth and analyses its trend to make an intelligent decision based on prevailing scenario. This decision is sent as a feedback to server which tries to match channel capacity and the sends the video at corresponding resolution and frames per second.

The client samples the incoming bit rate and monitors the pattern with an aim to analyze and predicts the near future bandwidth. The server is notified with the predicted link capacity which in turn responds with content adaptation process. The bit rates of packets are related to a time series model where a set of data points denotes the bit rates over successive time. The sampled data are arranged in a proper chronological order continuously and the past observations are analyzed to develop a mathematical model (ABBA algorithm) that captures the underlying data to make strategic decisions. This parametric approach considers that the underlying stochastic process has a certain structure which can be described using two parameters: auto-correlations and auto-covariance to forecast the future bit rates using regression.

3.2.1.1 Sender Sub-modules

The server's main job is to acquire the media content live from the camera or fetch from a memory location in case of a stored video. The following modules represent the workflow of streaming at the server side (Fig. 3.1).

a) *Init*: This module initializes the VLCJ player and identifies the media locator required for transmission.
b) *Stream*: It is used to establish connection with the requesting client using sockets while creating instance of player to stream at required quality.
c) *Adapt*: This module receives message from the client and uses this feedback to adapt to the network prevailing conditions by interpreting the data from client to make a strategic decision.

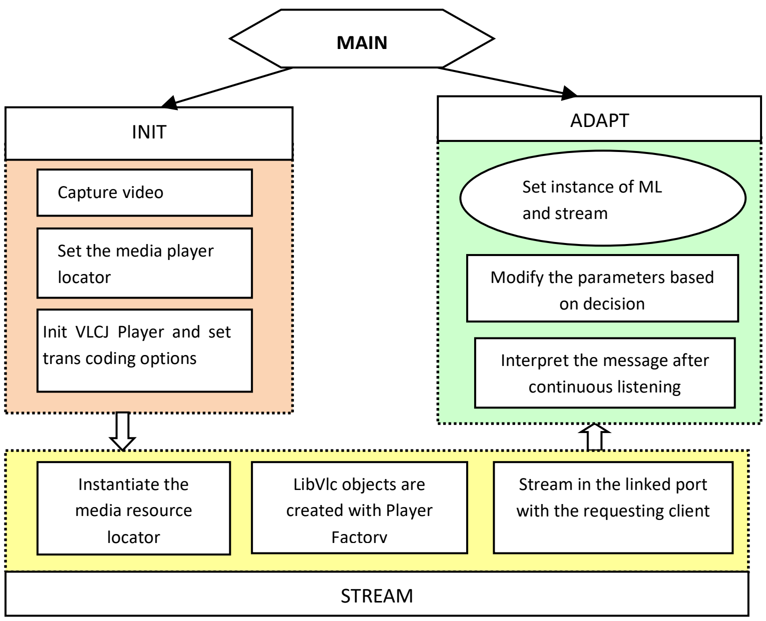


Figure 3.1. Server side modules

3.2.1.2 Receiver Sub-modules

The following modules illustrate how the client analyses (Fig. 3.2) the link instability based on ABBA Algorithm.

a) *Playback*: The client requests the sender to start streaming and initiates connection with the sender in an appropriate port using HTTP.
b) *Analyze*: The client analyzes the incoming bit rate of packets to ascertain how the link will support stream in near future using ABBA algorithm.
c) *Send Feedback*: The client creates a message based on defined format of feedback and makes an intelligent decision to alert the sender.

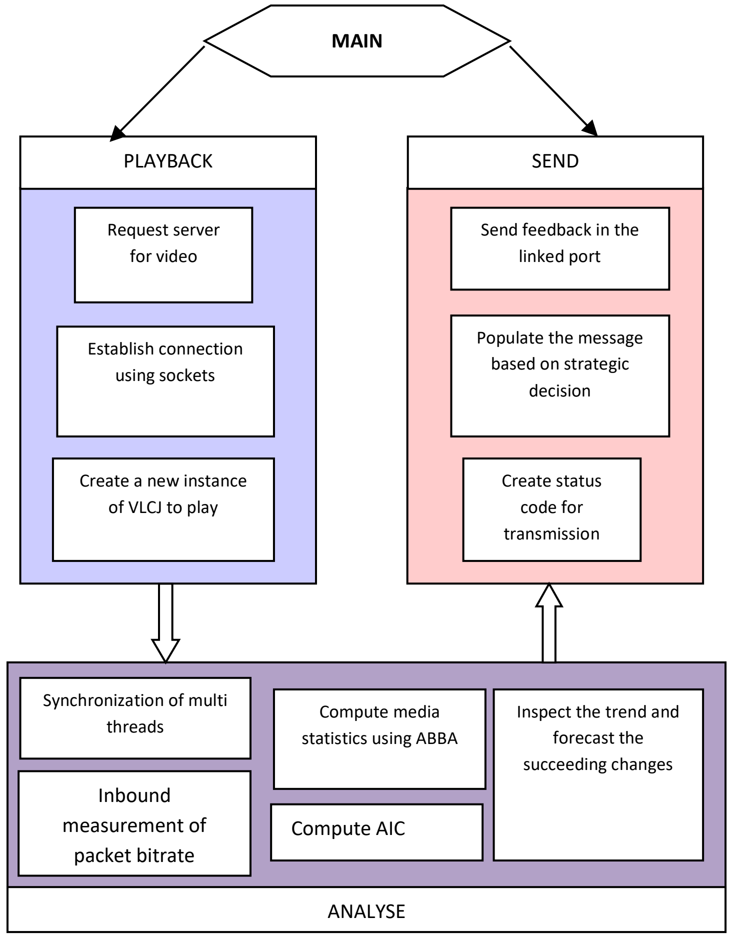


Figure 3.2 Client side modules

3.3 SYSTEM MODEL

The client side of the proposed system has higher complexity than the server, and it applies stream analysis algorithm to handle the non-linearity in the incoming traffic as they may vary rapidly over time that is too complicated to fit into any specific predefined classes. A heuristic based stochastic algorithm is formulated to overcome the existing problems and ensure delivery of higher quality videos in the prevailing circumstances. Based on the predicted link behavior the client identifies the trend of the series that is labeled as i. Advancing, ii. Degrading, iii. Oscillating, and iv. Stable. The traffic load in the network could momentary increase/decrease or prolong to increase/decrease. The projected incoming flow rate is then sent to the server as a feedback for it to adapt effectively and modify its parameters instantaneously.

3.3.1 Stochastic Prediction Model

There is need to explore a suitable statistical model which captures the dynamics of incoming bit rate and maps to a time series model that can be used to predict the future trend considering the current network conditions.

3.3.1.1 Auto-regressive (AR) Component

The Auto-regressive (AR) part is used to establish the covariance between the bit rates fluctuating over time [29] that can be used to foresee how the variations would take place in the future.

$$Auto\_Reg = 1 - \sum_{i=1}^{p} \phi_i L_i \qquad (3.1)$$

Where ϕ_i represent covariance and L_i lag operator for i^{th} packet, and p denotes the number of bit rate samples taken over time.

The covariance ϕ_i signifies a statistical relationship between bit rate and time that is used for trend analysis and foresees the upcoming bit rates, which is expressed as:

$$\phi = E\left[X_t, X_s\right] - \mu_t \times \mu_s \qquad (3.2)$$

Where μ_t and μ_s represents the mean associated with the random variables X_t and X_s.

3.3.1.2 Auto Regressive Integrated Moving Average (ARIMA) Model

Considering X_{tp} to be predicted bit rate where '*tp*' denotes the index number, *ARMA(p,q)* model with the integration of correlation factors is defined as:

$$\left(1 - \sum_{i=1}^{p'} \alpha_i L^i\right) X_{tp} = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t \qquad (3.3)$$

Where L^i is the lag operator, α_i is the autoregressive part (Auto_Reg) and θ_i is the moving average part (*Mov_Avg*) of the model linking the correlation between the successive time windows under evaluation for the i^{th} packet.

Now, the *Auto_Reg* polynomial would have a unitary root of multiplicity d when applied to a non-linear stochastic process where the first order differencing of a characteristic equation is non-stationary as

$$\left(1 - \sum_{i=1}^{p'} \alpha_i L^i\right) = \left(1 - \sum_{i=1}^{p'-d} \phi_i L^i\right) (1 - L)^d \qquad (3.4)$$

The stationarity here refers to the time series bit rate based model whose variance and auto correlation structures do not vary over time.

Integrating polynomial (3.4) with the Moving Average component (Mov_Avg) [30] to determine the future sequence by factorization of $p = p' - d$ would give rise to ARIMA model as

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d X_{tp} = \left(1+\sum_{i=1}^{q}\theta_i L^i\right) \tag{3.5}$$

The ARIMA in (3.5) can be generalized by adding a stochastic drift constant δ that denotes the change of average of bit rates in a continuously changing process that is modeled as a regression drift constant given by

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d X_{tp} = \delta + \left(1+\sum_{i=1}^{q}\theta_i L^i\right) \tag{3.6}$$

Now, the near future bit rates X_{tp} and trend of bandwidth fluctuations can be predicted to notify the server so that it can adapt accordingly as in (3.7) that integrate the correlation and variance into a form of regression.

$$X_{tp} = \delta' + \left(1+\sum_{i=1}^{q}\theta_i L^i\right) / \left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d \tag{3.7}$$

$$\text{Where } \delta' = \delta / \left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d \tag{3.8}$$

3.4. ALGORITHM DEVELOPMENT

There is a need for a standard benchmark criterion to ascertain if the model predicts relatively accurate value and in this context the Akaike Information Criteria (AIC) [31-32], is embedded in the proposed ABBA algorithm which helps in fine-tuning the quality of prediction model. The AIC act as a quality gauge in mathematical models using statistical parameters that computes the quality of a single model which is used as one of decision parameter.

To compare the performance of the ABBA algorithm, two existing approaches: (i) Buffer Switching Rate (BSR) adaptation, and (ii) Heuristic Decision based Rate Adaptation (HDR) method is formulated and presented here.

3.4.1 ARIMA Bitrate Based Adaptation (ABBA) Algorithm

The sliding window size used for analysis can be incremented using a constant factor *inc_fac* that could be predefined to overcome the stationarity issues based on the sample data points taken into consideration.

ABBA Algorithm:

Input: Bit Rates of packets for a Period of Time
Output: Forecasted Bit Rate for the next sequence of packets

1. Start streaming of video content
2. Sample the data rate by choosing a sequence of packets
3. Initialize *N*, *inc_factor*, *p*, *q*, *d*, *k* for *AIC*.
4. Compute μ_r, μ_s, μ_t. *// Calculate mean*
5. While (*i*<*N*) *// Take N samples*
6. If (μ_r = = μ_s) *//Test for stationarity*
7. If (C_{xx}(r,s) == C_{xx}(r-1, s-1)) *//* C_{xx} *is the covariance*
8. *N* = *N* + *inc_factor // Increment window size*
9. for *i* = 1 to *m*

$$a(L)X_t = X_t - \sum_{i=1}^{d} a_i X_{t-i}$$

10. Evaluate the Lag Operator
11. Evaluate the variance σ_s and σ_r

$$\sigma = \frac{\sum_{i=1}^{n}(X_i - X_{avg})^2}{n-1}$$

12. Compute θ as stated in (3.1) *// Moving Average*
13. for *j*=1 to *q* *// q is no of sample points chosen*
14. Evaluate *Auto_Corr* = θ * *L* *// Correlation*
14. if (*Auto_Corr*!=0)
15. Compute Φ as shown in (3.2) *// Auto Regression*
16. for *k*=1 to *p*
17. Evaluate *Auto_Var* = Φ * *L* *// Covariance*
18. if (*Auto_Var*>0)
19. Compute the forecasted X_{tp} using (3.7)
20. Compute variance as shown

$$\sigma_{(AIC)} = \frac{\sum_{i=1}^{n}(X_i - X_{tp})^2}{n-1}$$

21. Calculate the Akaike Information Criteria

$$AIC[i] = \log \sigma + \frac{2K}{N}$$

22. else
23. *N*= *N* + *inc_factor* *//Increment Window size*
24. end for
25. Find the *p,q,d* that corresponds to the maximum $\{\text{AIC}[i]\}_{\max}$ in the array
26. Designate the optimal values for *p*, *q*, *d* and repeat from Step 9.
27. Repeat from step 5 until streaming occurs.

3.4.2 Buffer Switching Rate (BSR) Adaptation Algorithm

Buffer based switching algorithm [33] considers the current buffer occupancy level and number of segments of video to provide the best possible quality of streamed video to the client. The harmonic mean is computed to measure the throughput for the entire video session and to avoid instantaneous variation of throughputs.

BSR Algorithm:

Input: Segment information, Current buffer occupancy level *Cur*, Weighted Harmonic mean download rate H_n

Output: The next predicted bit rate l_{n+1}

1. Read the current buffer occupancy level *Cur* for n^{th} segment while streaming
2. If ($Cur \le E_1$) *//Speedy start phase*
3. $l_{n+1} = r_1$ *//Choose lowest quality*
4. else
5. if $\left(\frac{s_{n+1}^{cur}}{H_n}\right) > cur - E_1$
6. $l_{n+1} = \max\left(r_{cur} > 0 \ , \ \frac{S_{n+1}}{H_n} \le cur - E_1\right)$
7. Set $d = 0$ *//immediate download*
8. else if ($Cur \le E_2$) *// progressive increase phase*
9. if $\frac{S_{n+1}}{H_n} < cur - E_2$
10. $l_{n+1} = r_{cur} + 1$ *//Increment resolution in steps*
11. else
12. $l_{n+1} = r_{cur}$ *// Maintain current level*
13. Set $d=0$
14. else if ($Cur \le E_3$) *// Rapid Shift Phase*
15. $l_{n+1} = \max\left(r_{cur} > E_2 \ , \ \frac{S_{n+1}}{H_n} \le cur - E_2\right)$
16. Set $d=cur-E_2$
17. elseif ($Cur>E_3$) *// Delayed download*
18. $l_{n+1} = \max\left(r_{cur} > E_3 \ , \ \frac{S_{+1}}{H_n} \le cur - E_2\right)$
19. Set $d = cur - E_2$
20. else
21. $l_{n+1} = r_{cur}$ *// Maintain current level*
22. Set $d=0$
23. Repeat the above steps until streaming terminates

3.4.3 Heuristic Decision based Rate Adaptation (HDR) Algorithm

Sample data set contains input variables being mapped to the set of membership functions using a fuzzy heuristic logic. The fuzzification technique involves the conversion of crisp value to continuous fuzzy value. The HDR algorithm is based on the decision of the heuristic control system which in turn is based on the if-then rules [24].

The difference in arrival time of the packets is classified as short (S), near (N) and extended (E) that describes the remoteness of the current buffering time from target buffering time *T*. This heuristic based rate adaptive decisions is used to avoid buffer underflow and also retain the difference between current and previous resolution quality to zero in order to avoid frequent variations .The buffering time is the difference between the time at which the packet is received and time at which it is played. The difference between the subsequent buffering times is classified as degrading (F), stable (S) and increasing (I). The rules corresponding to Decrease (D), Short Decrease (SD), Steady (S), Sort Advance (SA), and Advance (A) are as follows:

(r_1): if (small) and (decreasing) then D
(r_2): if (near) and (decreasing) then SD
(r_3): if (extended) and (decreasing) then S
(r_4): if (small) and (stable) then SD
(r_5): if (near) and (stable) then S
(r_6): if (extended) and (stable) then SA
(r_7): if (small) and (increasing) then S
(r_8): if (near) and (increasing) then SA
(r_9): if (extended) and (increasing) then A

These are five decision conditions which are sent to the server to make appropriate adjustment in parameters of the video being streamed. Finally, the centroid method is used for de-fuzzification i.e., to map the arrival and buffering times in terms of a single parameter *h* given by [25].

$$h = \frac{N_2 * D + N_1 * SD + Z * S + P_1 * SA + P_2 * A}{SD + D + S + A + SA} \tag{3.9}$$

Where N_2 , N_1, Z, P_1, P_2 are the membership values defined as in Table 3.2 [7] and *A*, *SA*, *S*, *SD*, and *D* are formulated in terms of rules (r_1 - r_9) given by

$$\begin{aligned} A &= \sqrt{r_9^2} \\ SA &= \sqrt{r_6^2 + r_8^2} \\ S &= \sqrt{r_3^2 + r_5^2 + r_7^2} \\ SD &= \sqrt{r_2^2 + r_4^2} \\ D &= \sqrt{r_1^2} \end{aligned} \tag{3.10}$$

Table 3.2. List of parameters in HDR [24]

Parameters	Value	Definition
T	35 sec	Target Buffering Time
d	60 sec	Time Period estimating connection throughput
N_2, N_1, Z, P_1, P_2	0.25, 0.5, 1, 1.5, 2	Factors of membership functions

3.5. IMPLEMENTATION ENVIRONMENT

Different video resolutions namely SQCIF, QCIF, CIF, QVGA, and VGA were used for the transcoding of the input video at the server side for every streaming instance. The frames per second (fps) designated for the streaming are 10, 15, 25, 30 and 35 respectively with the default value set to 25 fps. Java programming environment was used as it is platform independent and supports VLCJ (VLC for Java). The VLCJ is an open source framework that is used for video streaming that enables the media content to get embedded in a Java Swing. Since this platform is completely open source there are many customizable options available that are deployed for obtaining the media statistics. Synchronization of multithreads is carried out for communication between the client and server for transfer of data. Transcoding of input stream i.e., the process of converting media object from one configuration to another, allows to switch between various resolutions at the server side. Dshow [34] is the API that is used to capture the video and process it for streaming in the appropriate format.

The wireless network for experimental set up was established through Airtel 4G LTE-TDD Hotspot [9] that demonstrated an average of 3.7 Mbps in downlink during real time testing although it is intended to support more than 8 Mbps as specified by the service provider. For case study the end-to-end link bandwidth was estimated with the help of an online tool Speedof.Me [19]. The client and server were implemented in Lenovo idea pad laptop which has Intel Core i5 processor having 4 GB RAM and Windows 7 Professional 64 bit operating system. The streaming of video was implemented on top of the HTTP with UDP as its underlying transport protocol.

3.5.1 Performance Evaluation Parameters

Since in our experimental set up original video sequence was readily available, the Full Reference (FR) metrics were employed to evaluate the system performance. Further, FR metrics provide the most accurate result as it is computed with direct reference to the original sequence. The commonly used FR parameters are: Peak Signal to Noise Ratio (PSNR), Structural Similarity (SSIM) index, Video Quality metric (VQM), Aligned PSNR (A-PSNR) etc. Although the conventional PSNR is relatively simple to compute it exhibits imprecise measurement when used to measure the quality of streamed video over wireless network. Since the packet loss in the wireless mobile network cannot be neglected, more complex metrics like A-PSNR, VQM, and different types of SSIM are employed for the evaluation of system.

3.6. RESULTS AND DISCUSSIONS

3.6.1 Peak Signal to Noise Ratio (PSNR) Measurement

The PSNR metric was evaluated offline on the data generated by a live stream during the experimentation for the three implemented algorithms. The proposed ABBA performs better as it well predicts the future trend and allows the video content as per the network conditions thereby minimizing the mean square error in the decoded frame at the receiver. Table 3.3 lists the PSNR values corresponding to the ABBA (proposed), BSR, and HDR algorithms. The ABBA algorithm exhibits a higher average PSNR, which is 21% and 12% higher than the buffer based (BSR) algorithm and Heuristic based (HDR) algorithm respectively.

Table 3.3. Comparison of PSNR values

#	ABBA (dB)	HDR (dB)	BSR (dB)	#	ABBA (dB)	HDR (dB)	BSR (dB)
1	36.01	24.26	24.50	11	35.03	27.86	31.54
2	36.35	32.26	24.25	12	35.03	27.69	31.07
3	35.11	32.25	36.10	13	32.04	35.69	31.21
4	34.11	35.10	29.28	14	36.35	35.97	31.92
5	35.11	29.28	28.32	15	36.35	25.21	25.73
6	33.11	28.32	31.22	16	37.35	35.54	27.69
7	35.125	24.50	31.38	17	34.37	27.69	27.75
8	35.116	34.38	27.54	18	36.53	35.02	29.85
9	35.32	34.22	27.46	19	37.37	35.62	31.98
10	35.066	27.29	31.97	20	31.24	36.19	32.04
Average(dB)					35.10	31.37	29.13

3.6.2 Structural Similarity (SSIM) Measurement

The SSIM index was computed for the three algorithms (ABBA, BSR, and HDR), and the proposed ABBA algorithm exhibited a higher value with an average of 0.9541 which is 9% higher than the buffer based algorithm 7% better than heuristic based algorithm.

The SSIM index on few decoded consecutive frames at receiver corresponding to ABBA, BSR, and HDR algorithms is plotted in Figure 3.3. The higher SSIM index for ABBA algorithm is a reward for the perceived video quality as there is need for the perseverance of luminance and contrast factors that are influenced by the distortions.

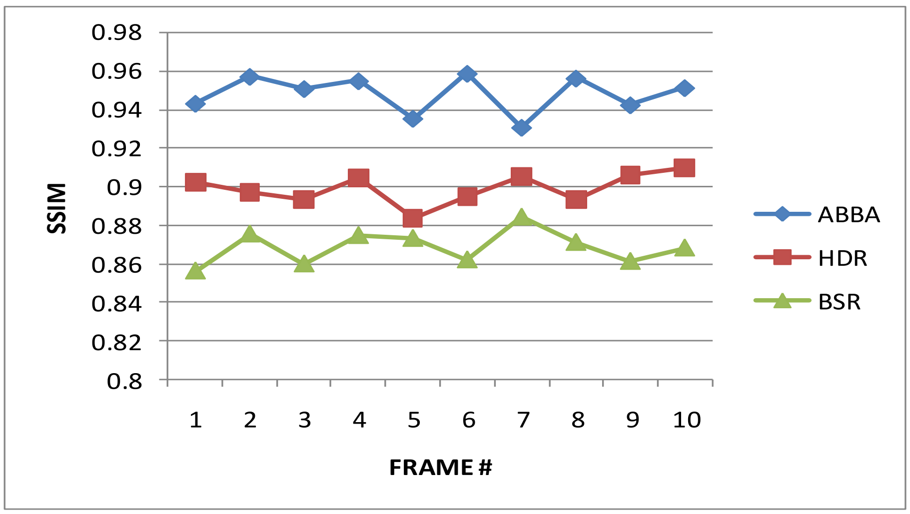


Figure 3.3. The SSIM index

3.6.3 Video Quality metric (VQM)

The VQM metric was employed to measure subjective quality assessment of the streamed video at receiver. Since the VQM score is the sum of many weighted parameters and its higher value represents the maximum loss of quality in the video, the lower values observed by the ABBA, HDR, and BSR is desirable. The ABBA based method shows 13% lower than the HDR and 17% lesser than the BSR scheme (Fig. 3.4) for the VQM measurement.

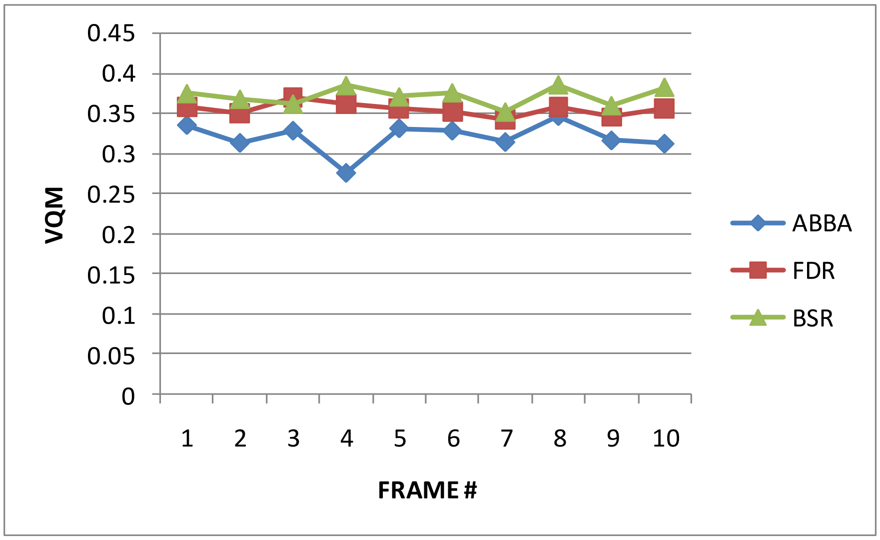


Figure 3.4. The VQM index

3.6.4 Aligned-Peak Signal to Noise Ratio (A-PSNR)

If there are multiple consecutive (say 5 and more) loss of frame in the wireless network, the conventional techniques like PSNR fails miserably due to application of fixed window model. This necessitates the adoption of new metric based on the dynamic window size. The Aligned-PSNR (A-PSNR) of ABBA algorithm produces 11.26% higher than the HDR, and 22.26% more than BSR algorithm (Fig. 3.5). The ABBA algorithm achieves the A-PSNR more than 30 dB which shows its usefulness in delivering high quality videos.

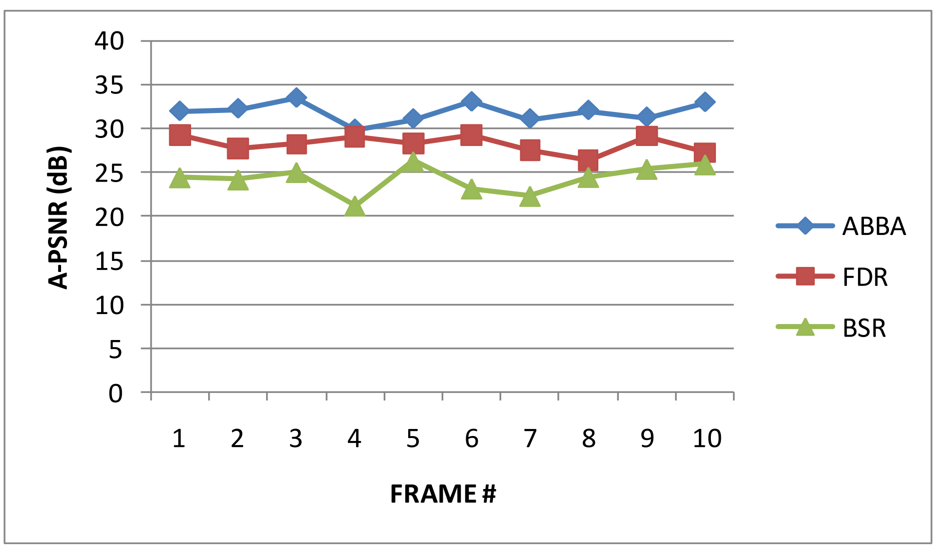


Figure 3.5. Aligned-PSNR values

3.6.5 Multi Scale- Structural Similarity (MS-SSIM) Index

A multi scale SSIM being more flexible than single scale metric provides better result with respect to correlations to human perceptions. On an average ABBA algorithm produces 2% higher quality on MS-SSIM scale than HDR and 0.7% higher than BSR method. Fig.3.6 shows the variation of MS-SSIM values on different consecutive frames. Although the improvement in quality by ABBA algorithm over other two is marginal, it still leads the pack.

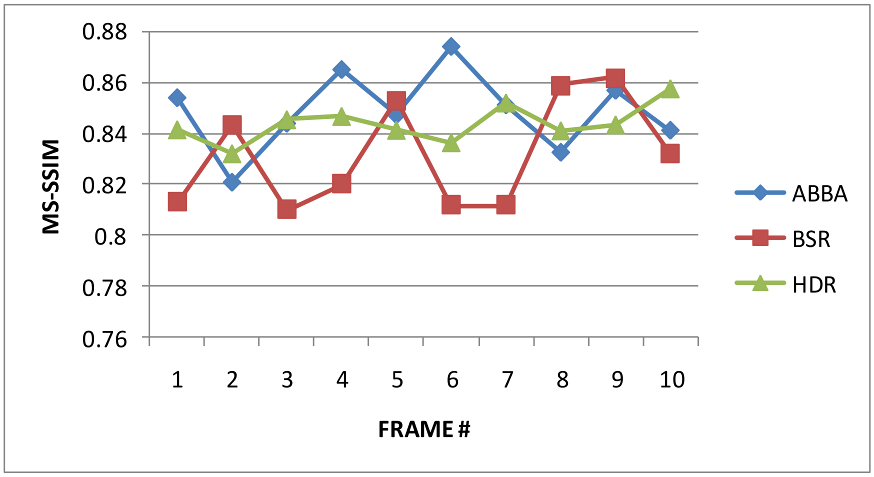


Figure 3.6. The Multi Scale SSIM observation

3.6.6 Inter Arrival Packet Delay

The inter arrival packet delay was observed on the Airtel 4G LTE-TDD network during live video streaming. As shown in Figure 3.7, an average delay of 45.2 milliseconds was observed during experimentation. Though the proposed algorithm does not directly deal with delay profile of the packet stream, it indicates the characteristics of the underlying network.

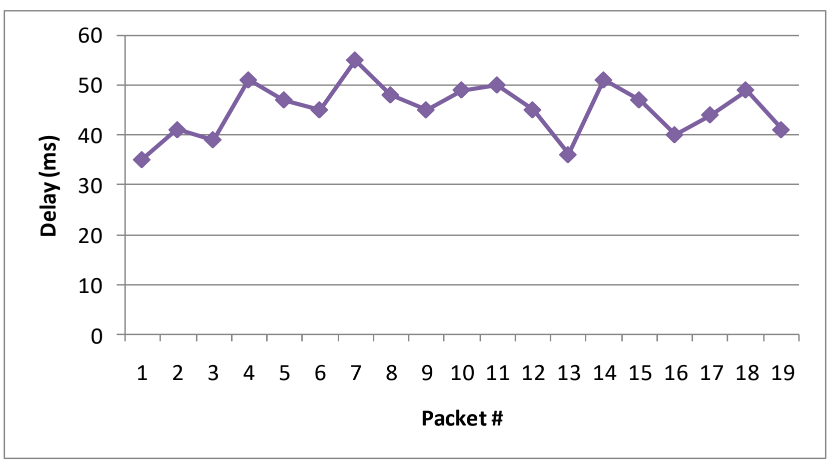


Figure 3.7. Inter Packet Delay for 20 packets.

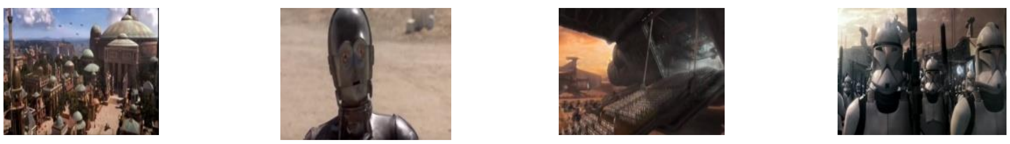
3.6.7 Visual Frames

The Figure 3.8 and 3.9, shows the few frames of the original and decoded sequences of video during experimentation of the live streaming and stored video streaming in the laboratory environment.

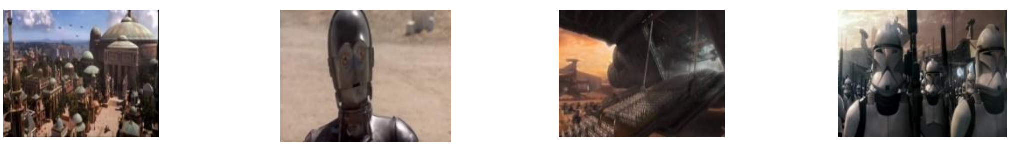
Original Frames

Decoded Frames

Figure 3.8. Live streaming from server to client



Original Frames



Decoded Frames

Figure 3.9. Stored Video Streaming for Entertainment

CHAPTER-4

MACHINE LEARNING BASED APPROACH

4.1 OVERVIEW

In the HTTP based Adaptive Streaming (HAS) based implementation, the selection of chunk duration directly effects the bit rate adaptation process. For example, a small chunk leads to a sub-optimal implementation, while a larger chunk will cause lack of adaptation in the fast changing internet traffic. The adoption of TCP/HTTP leads to an inefficient network bandwidth utilization, and a mismatch between the specified quality of a chunk and the actual encoding rate further aggravate the problem [35].

The bit rate adaptation algorithm needs to deal with multi-dimensional aspects of video streaming over HTTP through wireless networks. Most video codec, e.g., High Efficiency Video Coding (HEVC), H.264/AVC etc., generates variable bit rate of encoded video. However, the meta-data of MPEG-DASH does not carry this which can be used by the client for adaptation process [36]. The existing HAS approach do not provide control of transfer rate of video data. In fact, the TCP controls the transmission rate of video chunk, which respond to the congestion in network connecting client and server [37]. The fluctuation in received signal strength in wireless network further inflicts the system capacity. In a typical multiple access cellular system, the data rate at user equipment depends on prevailing channel conditions [38]. Most of the earlier work tries to estimate the future bandwidth and hence the efficiency of this approach depends on accuracy of prediction. However, it is inherently difficult to predict the receiving bit rate based on past history [39].

A machine learning technique can be employed in adaptation process provided it is incorporated into feedback quality loop. Reinforcement Learning (RL) [40] is an efficient solution for environmental learning problem. In RL, rather than relying on a fixed algorithm, learning agents can try different actions and gradually learn the best strategy for each situation. By continuous learning the RL algorithms like Q-learning can adapt to the changing conditions of the streaming system. However, the complexity of the model based on Q-learning [41] could seriously downgrade the system performance especially in dealing with the live streaming of video.

The Full Reference (FR) metrics [42] of video quality evaluation produces best result as it compares the received signal with original at frame level. However using FR metrics in dynamic adaptation of quality is not practical as the receiver does not have the original video. If the learning technique can be incorporated into No Reference (NR) metrics of video quality estimation, a dynamic streaming system can be designed and developed to deal with the client's terminal requirement. Although, the ITU-T G.1070

[43] recommendation is targeted towards quality of experience / service (QoE/QoS) planners in video telephony, its parametric model is adapted here in supporting video streaming system to meet the end to end service quality.

In this chapter, we propose a new algorithm based on RL approach called, State Action Reward State Action (SARSA) Based Quality Adaptation using Softmax Policy (SBQA-SP) algorithm to manage the adaptive streaming using NR metrics. SARSA is an online policy approach of RL [44], which doesn't require a separate learning and deployment phase. In SBQA-SP, the system is characterised by a set of states and the algorithm decides the suitable action to be taken based on the current state. The SBQA-SP identifies the current state of the system and based on the state chooses an action to perform. It calculates the reward as a result of the action performed and determines the resulting state of the system after the action. Next, the SBQA-SP determines the future action to be performed based on the Softmax exploration policy and update the Q-matrix. The chosen action is sent as feedback to the server.

To analyse the performance of the proposed approach, it is compared with other two approaches, namely (i) Q-Learning Based Quality Adaptation (QBQA) [41], and (ii) SBQA using ε-Greedy Policy (SBQA-GP). In QBQA, Q-learning method is used for controlling video quality adaptation. The Q-Learning approach is similar to SARSA, expect for the fact that it is an off-line policy algorithm which requires a learning and deployment phase. Also, the formula to update Q-matrix varies for SARSA and Q-learning. SBQA-GP is a variant of SBQA-SP approach in which ε-Greedy policy is used in selecting the best possible future action.

The proposed algorithms were implemented in accordance with the ITU-T J.247 recommendation (Table 1) which describes about "objective perceptual video quality measurement" [20].

4.2. PROPOSED SYSTEM

4.2.1. System Architecture

The architecture diagram of the proposed system is illustrated in Fig 4.1. It works on the top of HTTP in a typical internet environment where the last mile connectivity between client and server is supported on a 4G wireless network. Initially, the client requests the Media Descriptor file from the server, and the server replies with the Media Descriptor *Sidecar* file containing default settings and video parameters. Once the server streams the video to the client, the client continuously monitors the streaming quality using proposed SARSA based quality adaptation algorithm to determine the corrective action to be taken by the server in the near future and send this decision as feedback to the server. The server adapts the streaming video quality accordingly to match the client's requirement. The Test Parameters for ITU-T J.247 is given in Table 4.1.

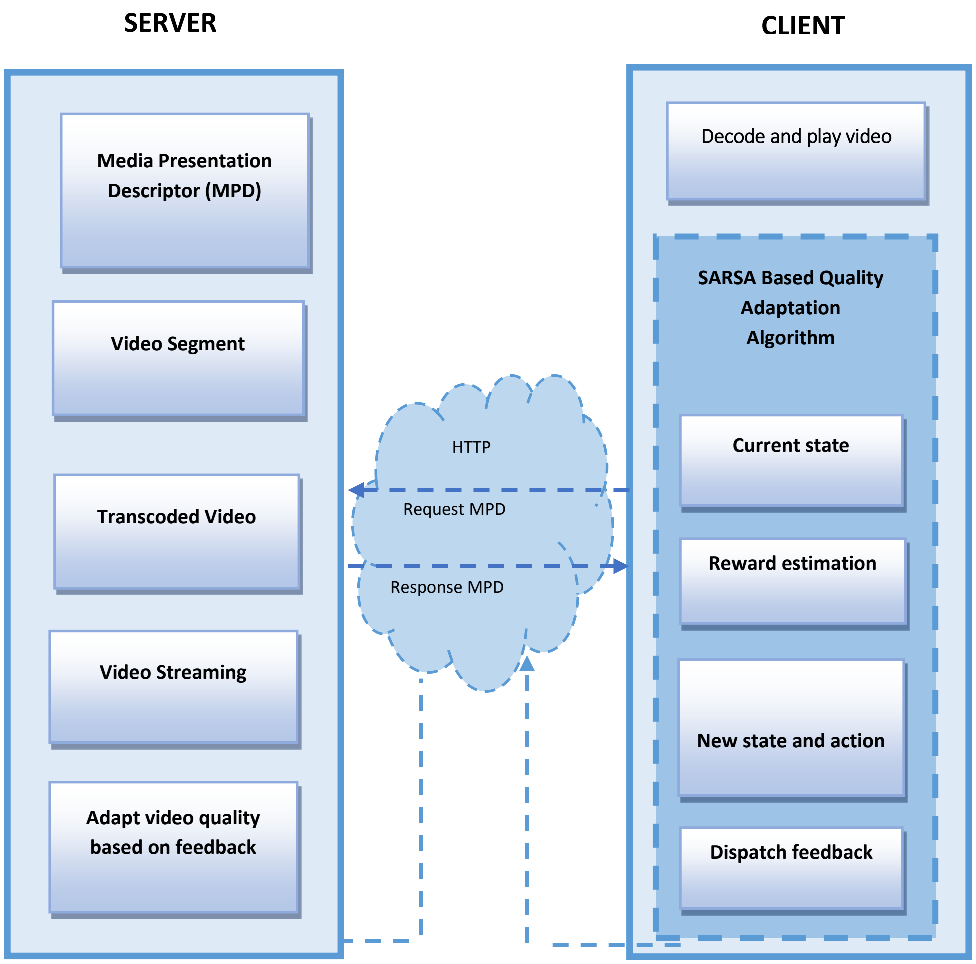


Figure 4.1. Architecture of the proposed work

Table 4.1.Test Parameters as per ITU-T J.247

S.No	Parameters	Values
1.	Transmission	Errors with packet loss
2.	Frame Rate	5 fps to 30 fps
3.	Video Codec	H.264/AVC (MPEG-4 part10),VC-1,Windows Media9, Real Video (RV 10),MPEG-4 Part 2
4.	Video Resolutions and bit rates	QCIF: 16 - 320 kbps CIF: 64 - 2000 kbps VGA: 128 - 4000 kbps
5.	Temporal errors (pausing with skipping)	Maximum of 2 seconds

4.2.2. Server Side Functions

The server initially set media locator URL either with location of the stored video or with the application program interface (*DirectShow* [34]) for accessing camera to capture live video. The media player / encoder object is initialized to perform video transcoding during streaming process. The variation of the frame rate is set between lower (e.g., 20 fps) and upper limit (e.g., 30 fps) and there solution is set with standards like QCIF, CIF etc. The destination address is linked with server's IP address and application's port number. Once the transcoding parameters are set, the server starts streaming at the specified URL through the HTTP port. It waits for client's reply in the application's port and connect with the client which request for connection. The server continuously listens for client feedback about the video quality, and then based on client's feedback adapt the video parameters. Now, the server's work can be outlined as: a) Video capture, b) Video transcoding, c) Video streaming, and d) Adapting video based on client's feedback.

4.2.3. Client Side Functions

The client initializes the media player component to decode and play the video. It specifies the streaming URL as a parameter to support media function, and connects with the server using sockets by specifying the IP address and port of server application. The client captures the packet using a packet capture framework. It calculates the throughput for certain period and assesses the frame rate (*fps*) and the bit rate at which the video need to be encoded at the server. The client also estimates the percentage of packet loss. Based on these three parameters, the video quality is estimated using ITU-T G.1070 parametric model. This is used for reward calculation in the proposed algorithm, and estimated throughput is assigned as the current state, and the video parameter is set to guide the current action. With the help of state, action, and reward, the SBQA algorithm determines the future action. This action is sent as the feedback to the server periodically.

4.3. ELEMENTS OF PROPOSED WORK

The SARSA based algorithm implemented at client forms the major part of the proposed algorithm. The different elements of SARSA approach used in quality and reward calculation represent the learning and adaptation process. No reference (NR) video quality metric is used as a reward function to guide the corrective actions.

4.3.1 Elements of SARSA Approach

a) *State:* It contains pertinent data about the environment conditions in a given time instance. In particular, the proposed model characterizes the state vector as $S_{cur} = \{T_h\}$ where T_h is the estimated throughput. The throughput values are mapped to different discrete finite state.

b) *Action*: Qualities are defined on the basis of analyzed data segment, and the quality segments are mapped to actions.

c) *Reward Function:* This function evaluates the fitness of the choice. The quality measurements through NR video metrics provide as the main input in reward calculation.

d) *Q-Table, Q(S, A):* The rows of this matrix represent the states of the system and each column contains one of the possible actions (the segment qualities). For a given pair (s, a), Q(·) indicates the learned benefit that the system will get in taking action *a* in state*s*. In order to formulate the client's learning and corresponding actions procedure, the SARSA approach updates Q-matrix after each quality decision as follows.

$$Q[s_{cur}, a_{cur}] \leftarrow Q[s_{cur}, a_{cur}] + \alpha\left[V_q + \gamma\, Q(s_{new}, a_{new}) - Q(s_{cur}, a_{cur})\right] \qquad 4.1$$

Where s_{cur} is the current state, a_{cur} is the selected action, $v_q$is the associated immediate reward, s_{new} is the next state after action a_{cur}, a_{new} is the action from state s_{new}. The learning rate (α) indicates how much the acquired information will affect to the old value of *Q(·)* in its updating, and the discount factor (γ) weighs the contribution of the immediate and future rewards ($0 \le \gamma \le 1$).

e) *Exploration Policy***:** Two exploration policies are taken into consideration here namely, Softmax and ε-Greedy.
Softmax policy chooses action by converting the action's expected reward to a probability. The action is chosen according to the resulting distribution, which is the Boltzmann distribution given by

$$P(a_j) = \frac{e^{-\frac{Q(s,a_j)}{r}}}{\sum_{i=1}^{|a_s|} e^{-\frac{Q(s,a_i)}{r}}} \qquad (4.2)$$

Where r is a positive parameter called temperature, and $a_s$is number of state of the system. High temperatures causeall actions to be nearly equiprobable, whereas low temperatures cause greedyaction selection.

With ε-greedy, the agent selects at each time step a random action with a fixed probability, $0 < \varepsilon < 1$, instead of selecting greedily one ofthe learned optimal actions with respect to the Q-function:

$$Action = \begin{Bmatrix} random\_action\_from\_A(s)\,, & if\; r < \varepsilon \\ argmax_{a\,\varepsilon\,A(s)} Q(s,a), & otherwise \end{Bmatrix} \qquad (4.3)$$

Where $0 < r < 1$ is a uniform random number drawn at each time step.

The SBQA approach is differentiated as two methods based on two exploration policies: SBQA using Softmax Policy (SBQA-SP), and SBQA using ε-Greedy Policy (SBQA-GP).

4.3.2 Video Quality Estimation using No-reference Metric

The ITU-T G.1070 defines a model [43] for estimating the video quality based on measurable parameters of IP network. The video quality (V_q) is represented as,

$$V_q = 1 + I_c I_t \tag{4.4}$$

Where I_c represents the basic video quality resulting from the encoding distortion due to the combined effect of bit rate and frame rate, I_t is the factor governed by degree of robustness due to packet loss.

I_c is expressed in terms of bit rate (b) and frame rate (f) according to equations (4.5 – 4.8) as follows.

$$I_c = I_0 \, e^{-\frac{(\ln(f) - \ln(f_0))^2}{2D_{Fr}^2}} \tag{4.5}$$

$$f_0 = v_1 + v_2 \, b \tag{4.6}$$

$$D_{Fr} = v_6 + v_7 \, b \tag{4.7}$$

$$I_0 = v_3 \left(1 - \frac{1}{1 + \left(\frac{b}{v_4}\right)^{v_5}} \right) \tag{4.8}$$

Where I_0 represents the maximum video quality ($0 < I_0 < 4$) at each video bit rate, f_0 is optimal frame rate ($1 < f_0 < 30$) maximizing the video quality at bit rate b,D_{Fr} isthe degree of video quality robustness due to frame rate.

I_t depends on packet loss robustness factor ($D_{P_{plv}}$)and rate of packet loss (p) given by

$$I_t = e^{-\frac{p}{D_{P_{plv}}}} \tag{4.9}$$

$$D_{P_{plv}} = v_{10} + v_{11} e^{-\frac{f}{v_8}} + v_{12} e^{-\frac{b}{v_9}} \tag{4.10}$$

Here $D_{P_{plv}}$represents the degree of video quality robustness against packet loss. The value of coefficients v_1, v_2, v_3,….v_{12} depends on type of codec, video format, interval between key frame, and size of video displayas mentioned in ITU-T G.1070.

4.4. PROPOSED ALGORITHM

4.4.1. SBQA USING SOFTMAX POLICY (SBQA-SP)

This approach uses Softmax exploration policy for action selection. The SBQA-SP algorithm is defined as follows.

SBQA-SP Algorithm

1. Initialize the number of packets *N*, learning rate α and discount factor γ, last state s_{last} and Q-matrix *Q*.
2. Compute throughput (*Th)* resulting from the capture of *N* packets.
3. Identify current state s_{cur} based on *Th* value.
4. Read the resolution *res*, and frame per second *fps* from the header in streamed video.
5. Determine current action a_{cur} based on the current quality segment.
6. While s_{cur}<s_{last} *// till last state reached*
7. Read the encoded bit rate *b*, and compute frame loss percentage *p*.
8. Calculate the reward (video quality) V_q using (4.4)
9. Estimate the current throughput Th_{cur} and based on Th_{cur} identify new state s_{new}.
10. Compute new action a_{new}← SoftMax(*Q*,*s*).
    // Exploration policy function to get best possible future action
11. Update the $Q[s_{cur}, a_{cur}]$ based on (4.1)
12. $s_{cur} \leftarrow s_{new}$//Update new state to the current state
13. $a_{cur} \leftarrow a_{new}$//Update new action to the current action
14. Assign action a_{cur} as feedback to the server
15. End
16. Go to Step 2 and continue till streaming occurs
17. End

Softmax (*Q*,*s*)

1. Initialize *r* = 1, *offset* = 0, *sum* = 0, *flag* = 0 and *prob[] = {0}*, $prob_{length}$ = length of *prob[]*
2. For *i* = 1 to $prob_{length}$
3. *prob[i]* = $e^{Q[s,i]/r}$ *// Access Q[s,i] in the Q matrix*
4. *sum* = *sum* + prob[i]
5. End
6. For *i* = 1 to $prob_{length}$
7. *prob[i] = prob[i]* / *sum*
8. End
9. Generate a random value *ran*, 0<*ran*<1 *// pointer for random action selection*
10. For *i* = 1 to $prob_{length}$
11. If *ran*>*offset* and *ran*<*offset* + *prob[i]*
12. *selectedAction* = i
13. *flag = 1*
14. *offset* = *offset* + *prob[i]*

15. End
16. If *flag = 0*
17. Repeat from step 9
18. Else
19. Return *selectedAction*

4.4.2. SBQA USING ε GREEDY POLICY (SBQA-GP)

SBQA-GP as a variant of SBQA-SP algorithm uses ε-greedy exploration policy for action selection. The method for selecting action using this policy is defined below.

ε-greedy (*Q,s*)

1. Initialize fixed probability ε and *max // Store maximum value (max) in* s^{th} *row of Q-matrix.*
2. Generate a random value *ran* in the range 0 to 1.
3. If *ran<ε*
4. *selectedAction* = -1
5. Else
6. For *i* = 1 to Q_{length} *// get* Q_{length} *from Q-matrix*
7. If *Q[s,i] >=max*
8. *selectedAction* = *i// action with max reward*
9. *max = Q[s,i]*
10. End
11. If *selectedAction* =-1
12. Generate a random number *r*, in range of action.
13. *selectedAction = r*
14. Return *selectedAction*

4.4.3. Q-LEARNING BASED QUALITY ADAPTATION (QBQA)

Q-Learning is a model free reinforcement learning algorithm. The QBQA is based on [44], where the authors have designed and optimized a Q-Learning approach for video quality adaptation. The system state (s_k) was modeled with Bandwidth (bw_k), Buffer occupancy level (buf_k), and quality level (q_{k-1}) of the segment. The action (a_k) of the system is based on different qualities of video segment which is expressed using nominal bit rate. The reward is formulated for the action taken by considering three factors which are quality affected by bandwidth and buffer, video freeze, and quality switching. The exploration policy used for action selection is value based differential Softmax. The adaptation algorithm based on Q-Learning [41] is as follows.

QBQA Algorithm

1. Initialize the learning rate α, discount factor γ, Q-matrix, and optimal bandwidth value B_{opt}.
2. Read the current buffer occupancy level buf_k for k^{th} segment and quality level q_{k-1} for segment k-1 while streaming
3. For i = 1 to t *//Training Phase*
4. Estimate the bandwidth bw_k
5. Assign s_k= { bw_k, buf_k, q_{k-1} } *// Current State*
6. a_k= Softmax(Q, s_k) *// Exploration policy function to get best possible action.*
7. Calculate the quality factor related to bandwidth and buffer occupancy level using the equation

$$R_{quality} = -1.5 \cdot \left| bw_k \cdot \frac{1+(buf_k/B_{opt})}{3-(bw_1/a_1)} - a_k \right| \quad (4.11)$$

8. Calculate the quality factor related to switch in quality using the equation

$$R_{switches} = -|q_{k-1} - a_k| \quad (4.12)$$

9. Read the duration of video freeze t_{stall} , time elapsed from the last freeze t_{play} and number of freezes n
10. Calculate the quality factor related to video freezing using the equation

$$R_{freezes} = \begin{cases} -100 \cdot \left| \frac{a_k}{bw_k} \cdot \frac{e^{\frac{t_{stall}}{10}}}{\ln(t_{play}+1)} \right| & a_k = a_1 \\ -100 \cdot \left| \frac{a_k}{bw_k} \cdot \frac{e^{n+\frac{t_{stall}}{10}}}{\ln(t_{play}+1)} \right| & a_k \neq a_1 \end{cases} \quad (4.13)$$

11. Calculate

$$R_{total} = R_{quality} + R_{switches} + R_{freezes} \quad (4.14)$$

12. End
13. Determine the resultant state, s_{k+1} using{ bw_{k+1}, buf_{k+1}, q_k}
14. Update the Q-matrix using

$$Q[s_k, a_k] \leftarrow (1-\alpha)\, Q[s_k, a_k] + \alpha\left[R_{total} + \gamma\, max_b Q(s_{k+1}, b)\right] \quad (4.15)$$

15. Estimate the bandwidth bw_k*//Testing Phase begins*
16. Assign s_k= { bw_k, buf_k, q_{k-1} }
17. a_k= $\max_a$ (Q(s_k, a))
18. Send a_k as feedback to the server.
19. Repeat from Step 15 until streaming occurs.

4.5. IMPLEMENTATION ENVIRONMENT

The Java programming environment based on 64bit JDK Version 7 was chosen for implementation purpose and the code was developed using Eclipse IDE. The 64 bit VLC media player was used for playing the media, as VLC can be easily manipulated using java with the help of VLCJ framework. *Dshow* API [34] was used for capturing live video for streaming, but for packet capturing *Jnetpcap* [45] framework was used.

The client and server were connected through4G Mobile Hotspot devices in a typical cellular wireless network. Frame rates were varied with values 20, 24, 27, 30 while default rate was chosen to be 24. Standard video resolutions like QCIF(176*144), CIF(352*288),VGA(640*480), SQCIF (128*96) and QVGA (320*240) were used dynamically at encoding / decoding process during the experiment.The server and client were implemented in Windows 10 (64 bit operating system) Core i3 processor with 8GB RAM and Windows 10, 64bit OS, Core i5 processor with 4GB RAM respectively. The streaming was implemented on top of the HTTP in a typical internet environment.

The network bit rate carrying capacity of the Airtel Mobile Hotspot (4G-LTE TDD) [9] dongle was analyzed using online tool *Speedof.me* [19] and one instance result is shown in Fig. 4.2. Internet speed of wireless connection was measured without using FLASH or java which is currently used by many other speed test websites. The online tool provided a broadband speed test service which uses pure browser capabilities such as HTML5 and JavaScript. For the reliability of measured data, it utilizes multiple test servers around the world and the server is chosen automatically. Both download and upload speed of the network device is observed independently.

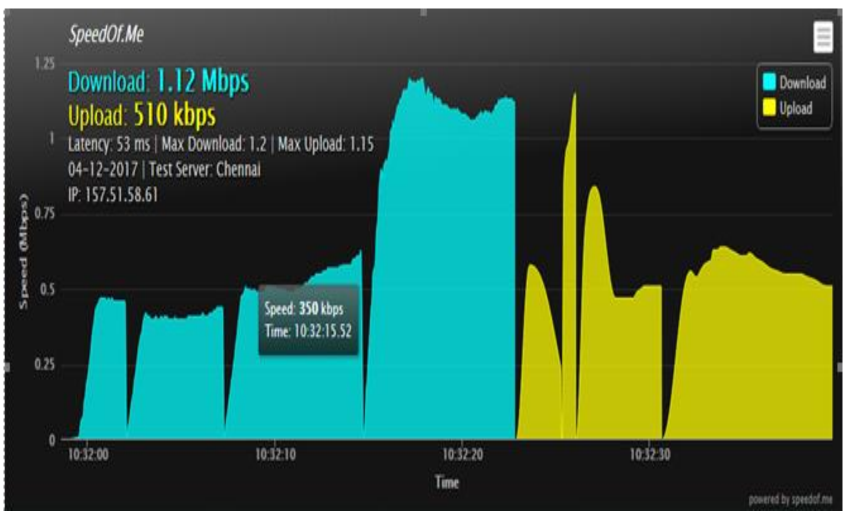


Figure 4.2. Bitrate observed during stream of live video using Airtel 4G LTE TD Hotspot

4.6. RESULTS AND DISCUSSION

The proposed approach SBQA-SP and its variant SBQA-GP along with existing QBQA algorithms were implemented and tested in typical internet environment. The system performance was evaluated using full reference video quality metrics: PSNR, SSIM, MS-SSIM and VQM. The numerical data representing different quality index arising out of live streaming of video were analyzed offline.

4.6.1. Peak Signal to Noise Ratio (PSNR)

The commonly used video / image quality metric PSNR is used here because it is fast and simple to implement. Fig. 4.3 depicts the PSNR values corresponding to the SBQA-SP, SBQA-GP and QBQA algorithms. The SBQA-SP algorithm exhibits a higher average PSNR, which is 8% and 5% higher than the SBQA-GP and QBQA algorithm respectively. The SBQA-SP performs better compared to other two approaches as it learns the environment conditions without any pre learning phase and adapts the video quality as data arrives. Also, the exploration policy used helps to convergence at a faster rate.

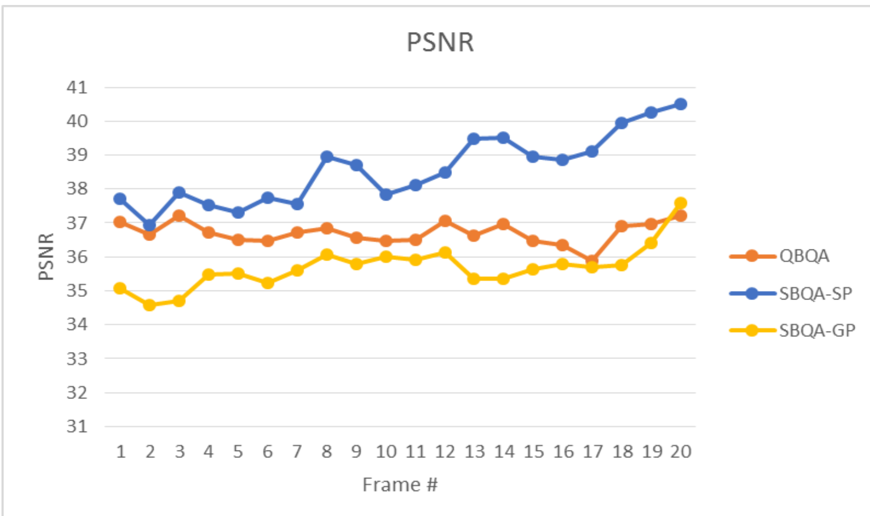


Figure 4.3. The PSNR observation

4.6.2. Structural Similarity Measurement (SSIM)

The SSIM index was computed for the three algorithms (SBQA-SP, SBQA-GP and QBQA), and the proposed SBQA-SP algorithm exhibited a higher value with an average index of 0.9940 which is 2% higher than the QBQA algorithm 3% better than SBQA-GP. The SSIM index on few decoded consecutive frames at receiver corresponding to three algorithms is plotted in Figure 4.4. The higher SSIM index for the proposed algorithm is a reward for the perceived video quality as there is need for the perseverance of luminance and contrast factors that are influenced by the distortions.

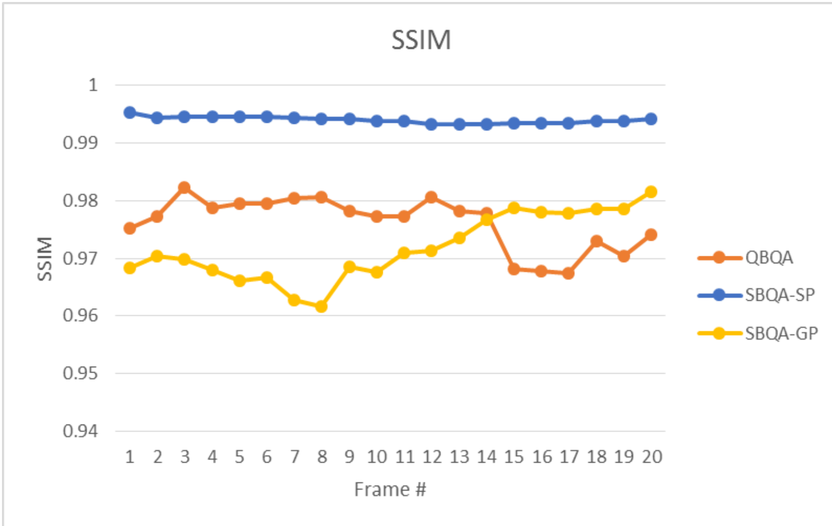


Figure 4.4. The SSIM index

4.6.3. Multi Scale Structural Similarity (MS-SSIM) Measurement

A multi scale SSIM being more flexible than single scale metric provides better result with respect to correlations to human perceptions. On an average SBQA-SP algorithm produces 1.2% higher quality on MS-SSIM scale than QBQA algorithm and 2.2% SBQA-GP algorithm. Fig. 4.5 shows the variation of MS-SSIM values on different consecutive frames. Although the improvement in quality by SBQA-SP algorithm over other two is marginal, it still leads the pack.

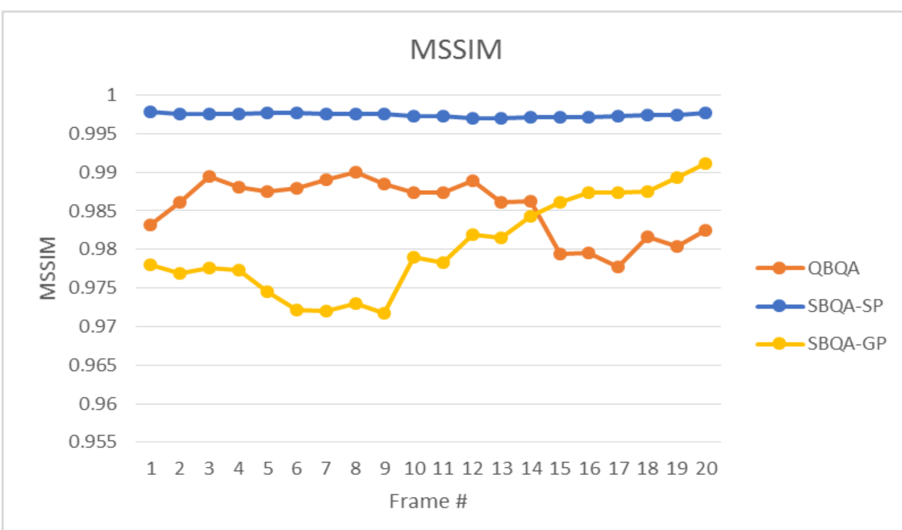


Figure 4.5. The Multi Scale SSIM index

4.6.4. Video Quality Metric (VQM)

The VQM is an important metric for the evaluation of video quality because it considers the spatial-temporal aspects of visual perception. Since the VQM score is the sum of many weighted parameters and its higher value represents the maximum loss of quality in the video, the lower values observed by the SBQA-SP, SBQA-GP and QBQA algorithms are desirable. The SBQA-SP based method shows 15% lower than the SBVQA-GP and 23% lesser than the QBQA algorithm. The VQM values for 20 Frames are depicted in Fig. 4.6.

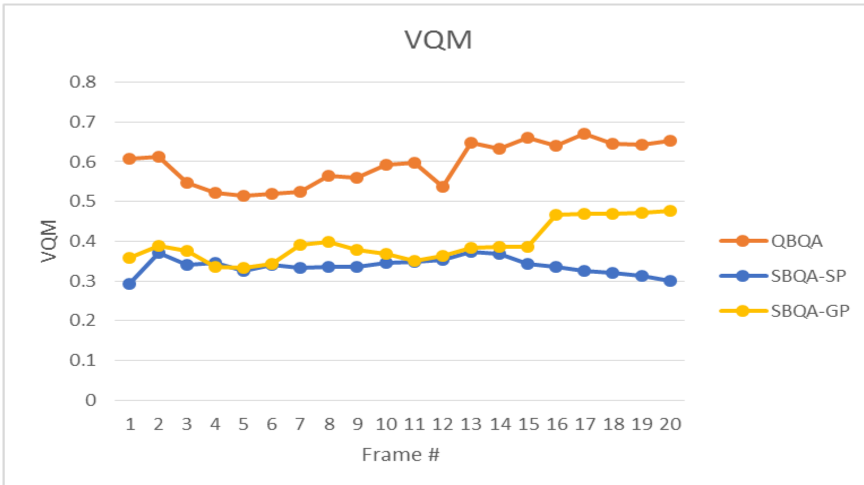


Figure 4.6. The VQM observation

4.6.5. Three-component Structural Similarity (3-SSIM) Measurement

The 3-SSIM is a form of SSIM that is calculated as a weighted average of SSIM for three categories of regions: edges, textures, and smooth regions. From Fig. 4.7, it is evident that the proposed SBQA-SP approach shows a higher 3-SSIM value compared to other approaches. The average values shows that SBQA-SP approach provides quality which is 0.4% higher than QBQA approach and 1.04% higher than SBQA-GP approach with respect to 3-SSIM scale.

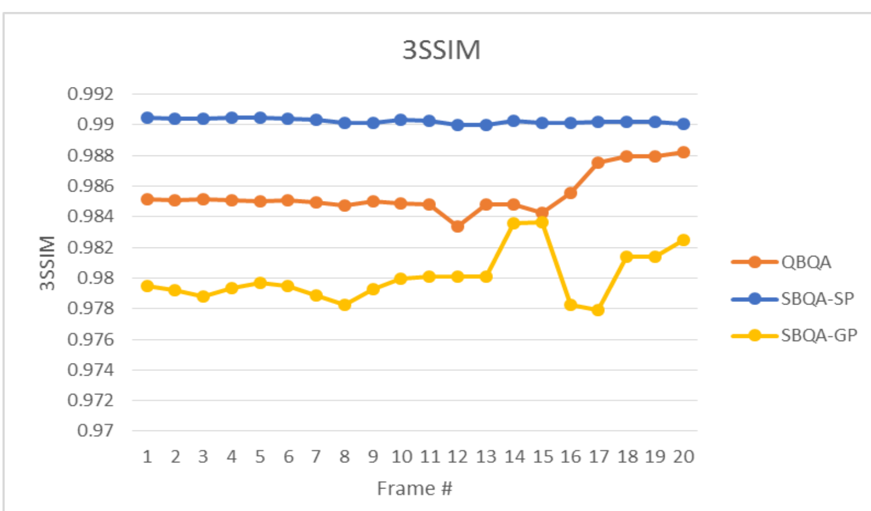


Figure 4.7. The 3-SSIMindex

4.6.6. Inter Arrival Packet Delay

The Fig. 4.8 shows the observed inter arrival packet delay on the Airtel 4G LTE-TD network during live video streaming. An average delay of 7.6 milliseconds was observed during the experimentation process.

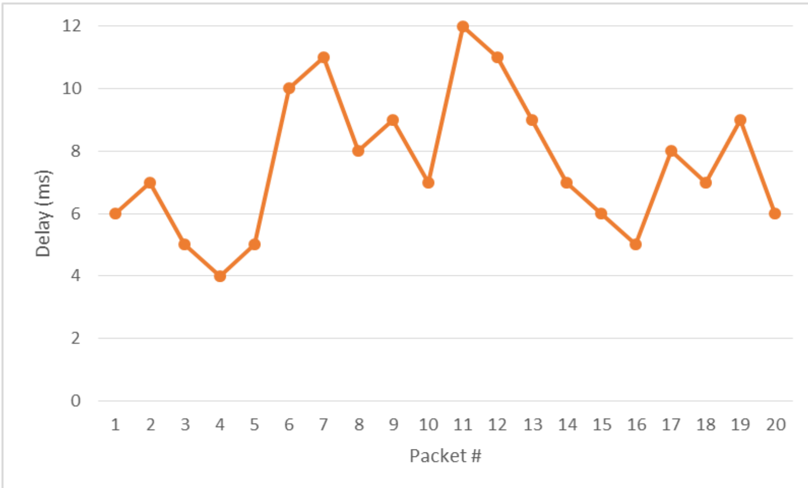
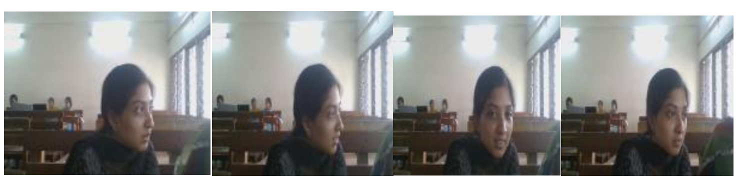


Figure 4.8. Inter packet delay

4.6.7. Experimental Original and Decoded Sequence of Frames

The Fig. 4.9 shows the few original and decoded video sequences captured during live streaming experiment at the server and client respectively. The display resolution is 640*480 with the frame rate of 24. The live video streaming was carried out in a class room environment. The codec used for encoding and decoding process is H.264 for live as well as stored video.



(a) Original

(b) Decoded

Figure 4.9. Live Streaming (few selected original and decoded frames)

CHAPTER-5

CONCLUSION & FUTURE WORK

5.1 CONCLUSION

The dynamic adaptive streaming over HTTP in a wireless paradigm was implemented for live and stored video scenarios considering the vulnerabilities of the medium, to withstand the fluctuations of widely varying link bit rates. This technology is found to have great potential to be used in the tele-medical video streaming. In one of the approaches, we used maxima minima concept and RMS approximation which tries to estimate the bit rate pattern in real-time which includes the fluctuation time in the network for dynamic adaptive streaming over HTTP. In another approach, the strategic decisions in real-time adaptation of video stream were based on the time series analysis of the streamed data, with an objective to achieve maximum obtainable quality. The ABBA algorithm implemented to achieve real-time adaptation of video stream was tested on different standard video quality metrics and the result showed an improvement over other two existing approaches (HDR and BSR algorithm) with acceptable quality index. Although the system is targeted towards cinematic video, it can also support tele-medicine applications where doctors can communicate to their peers. The concept of HTTP adaptive streaming through 4G wireless network implemented using Q-learning with NR metrics for live video considering the challenges due to varying wireless link condition and internet traffic achieved maximum obtainable quality. The decisions that are made to adapt video quality in a real time video streaming were based on the current state of the system and the action to be taken in that state maximizes the reward. The proposed SBQA-SP algorithm using Softmax policy was formulated and implemented using ITU-T G.1070 model for no-reference metrics quality evaluation. All these techniques are client server based networks, so it can be easily implemented as it runs on the top of the http.

5.2 FUTURE WORK

The work can be extended further by incorporating other aspects like sudden network congestion, as it may cause extra delay on streaming packets, which is undesirable in real-time tele-medical application. The ITU-T G.1070 standard employed in the project, is targeted at QoE / QoS in video telephony, which constrains in achieving higher quality of streaming video in an IP network, so a suitable mechanism is required to enhance the system performance. Further, the proposed works was implemented and tested in one way communication, which can be extended to two-way video streaming.

REFERENCES

[1]. 3GPP Specification, “3GPP, Transparent End-To-End Packet-switched Streaming Service (PSS): Progressive Download and Dynamic Adaptive Streaming over HTTP (3GP-DASH)”, Release 12, Document # TS 26.247, 2015.

[2]. Mincheng Zhao, Xiangyang Gong, Jie Liang, Wendong Wang, Xirong Que, and Shiduan Cheng, “QoE-Driven Cross-Layer Optimization for Wireless Dynamic Adaptive Streaming of Scalable Videos Over HTTP”, IEEE Transactions on Circuits and Systems for Video Technology, Vol. 25, No. 3, March 2015, pp.451-465.

[3]. Stefano Petrangeli, Tim Wauters, Rafael Huysegemsy, Tom Bostoeny, and Filip De Turck, “Network-based Dynamic Prioritization of HTTP Adaptive Streams to Avoid Video Freezes”, IEEE/IFIP International Workshop on Quality of Experience Centric Management, May 11-15, 2015.

[4]. Shuangwu Chen, Jian Yang, Member, Yongyi Ran, and Enzhong Yang, “Adaptive Layer Switching Algorithm Based on Buffer Underflow Probability for Scalable Video Streaming Over Wireless Networks”, IEEE Transactions on Circuits and Systems for Video Technology, Year 2015.

[5]. Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2015–2020, February 3, 2016.

[6]. Luca De Cicco, "An Adaptive Video Streaming Control System: Modeling, Validation, and Performance Evaluation", IEEE/ACM Transactions on Networking, Volume 22, Issue 2, pp.526-539, April 2014.

[7]. Jan Willem Kleinrouweler, “Modeling Stability and Bitrate of Network-Assisted HTTP Adaptive Streaming Players”, International Tele traffic Congress (ITC 27), Ghent, pp-177–184, 2015.

[8]. Dhananjay Kumar, Nandha Kishore, Easwaran, A. Srinivasan, A. J. Manoj Shankar L., Arun Raj, "Adaptive Video Streaming Over Http Through 3g/4g Wireless Networks Employing Dynamic On The Fly Bitrate Analysis", ITU Kaleidoscope: Trust in the Information Society, Barcelona, December 2015.

[9]. “Airtel 4G Wi-Fi Hotspot”. [Online]. Available at: http://www.airtel.in/4g/index.

[10]. ITU-T Recommendation Series J, “Objective Perceptual Multimedia Video Quality Measurement in the Presence of a Full Reference”, document # J.247, August 2008.

[11]. Junchen Jiang, Vyas Sekar, and Hui Zhang, “Improving Fairness, Efficiency, and Stability in HTTP-Based Adaptive Video Streaming With FESTIVE”, IEEE/ACM Transactions on Networking, Vol.22, No.1, February 2014, pp.326-340.

[12]. Yuedong Xu, Yipeng Zhou, and Dah-Ming Chiu, “Analytical QoE Models for Bit-Rate Switching in Dynamic Adaptive Streaming Systems”, IEEE Transaction on Mobile Computing, Vol.13, No.12, December 2014, pp. 2734-2748.

[13]. Hung T. Le, Duc V. Nguyen, Nam Pham Ngoc, Anh T. Pham, and Truong Cong Thang, “Buffer-based Bitrate Adaptation for Adaptive HTTP Streaming”, The 2013 International Conference on Advanced Technologies for Communications (ATC'13), 16 - 18 Oct. 2013, pp. 33 – 38.

[14]. Min Xing, Siyuan Xiang, and Lin Cai, “A Real-Time Adaptive Algorithm for Video Streaming over Multiple Wireless Access Networks”, IEEE Journal on Selected Areas in Communications, Vol.32, No.4, April 2014, pp.795-805.

[15]. Yunmin Go, Oh Chan Kwon, and Hwangjun Song, “An Energy-efficient HTTP Adaptive Video Streaming with Networking Cost Constraint over Heterogeneous Wireless Networks”, IEEE Transaction on Multimedia, Year 2015.

[16]. Zhi Li, Xiaoqing Zhu, Joshua Gahm, Rong Pan, Hao Hu, Ali C. Begen, and David Oran, “Probe and Adapt: Rate Adaptation for HTTP Video Streaming At Scale”, IEEE Journal on Selected Areas in Communications, Vol.32, No. 4, April 2014.

[17]. Maxim Claeys, Steven Latr´e, Jeroen Famaey, and Filip De Turck “Design and Evaluation of a Self-Learning HTTP Adaptive Video Streaming Client” in IEEE Communication Letters, Vol.18, No.4, April 2014, pp.716-719.

[18]. http://www.rcom.co.in/Rcom/personal/internet/wireless_internet.html

[19]. “HTML5 Speed Test”. [Online]. Available at: http://speedof.me/.

[20]. ITU-T Recommendation Series J, “Objective Perceptual Multimedia Video Quality Measurement in the Presence of a Full Reference”, document # J.247, August 2008.

[21]. ISO/IEC JTC1/SC29/WG11 and ITU-T SG16 Q.6, “New Video Quality Metrics in the H.264 Reference Software”, document # JVT-AB031, July, 2008.

[22]. Anush K. Moorthy and Alan C. Bovik, “Efficient Motion Weighted Spatio-Temporal Video SSIM Index”, Proc. SPIE 7527, Human Vision and Electronic Imaging XV, 75271I, February 17, 2010.

[23]. https://media.xiph.org/video/derf/

[24]. Angelos Michalas, Aggeliki Sgora, Dimitrios D. Vergados,"FDASH: A Fuzzy-Based MPEG/DASH Adaptation Algorithm”, IEEE Systems Journal, Volume 10, Number 2, pp.859-868, June 2016.

[25]. Parikshit Juluri, Venkatesh Tamarapalli, “SARA: Segment aware rate adaptation algorithm for dynamic adaptive streaming over HTTP”, IEEE International Conference on Communication Workshop (ICCW), pp 1765-1770, June 2015.

[26]. ITU-T Recommendation Series Y, “Global Information Infrastructure, Internet Protocol Aspects and Next generation Networks”, document # Y.1540, March 2011.

[27]. ITU-T Recommendation Series J, “Reference algorithm for computing peak signal to noise ratio of a processed video sequence with compensation for constant spatial shifts, constant temporal shift, and constant luminance gain and offset”, document # J.340, June 2010.

[28]. ITU-T Recommendation Series J,” Method for specifying accuracy and cross-calibration of Video Quality Metrics (VQM) ”, document # J.149, March 2004.

[29]. Huda M. A. El Hag, Sami M. Sharif, "An adjusted ARIMA model for internet traffic", IEEE Africon, Windhoek, pp.1-6, September 2007.

[30]. Tano, Subanar, "New procedure for determining order of subset autoregressive integrated moving average (ARIMA) based on over-fitting concept", International Conference on Statistics in Science, Business, and Engineering (ICSSBE), Langkawi, pp 1-5, Sep 2012.

[31]. Liang Wang and Gaetan A. Libert, "Combining Pattern Recognition Techniques with Akaike’s Information Criteria for Identifying ARMA Models", IEEE Transactions On Signal Processing, Vol. 42, No. 6, June 1994.

[32]. Seghouane, Canberra Res, “The Akaike Information Criterion With Parameter Uncertainty”, Fourth IEEE Workshop on Sensor Array and Multichannel Processing, Waltham, pp.430-434, July 2006.

[33]. Parikshit Juluri, Venkatesh Tamarapalli, “SARA: Segment aware rate adaptation algorithm for dynamic adaptive streaming over HTTP”, IEEE International Conference on Communication Workshop (ICCW), pp 1765-1770, June 2015.

[34]. “DirectShow (Windows)”. [Online]. Available at:https://msdn.microsoft.com/enus/library/windows/desktop/dd375454(v=vs.85).aspx

[35]. Sangwook Bae, Dahyun Jang, and KyoungSoo Park, “Why Is HTTP Adaptive Streaming So Hard?”, Proc. of the 6thAsia- Pacific Workshop on Systems (APSys '15), Tokyo, July 27-28, 2015.

[36]. Li Yu, TammamTillo, and Jimin Xiao, “QoE-Driven Dynamic Adaptive Video Streaming Strategy With Future Information”, IEEE Transactions on Broadcasting, Issue 99, pp 1-12, April 2017.

[37]. Guibin Tian and Yong Liu (2015), “Towards Agile and Smooth Video Adaptation in HTTP AdaptiveStreaming”, IEEE/ACM Transactions On Networking, Sept 2015.

[38]. Sergio Cicalò, NesrineChanguel, VelioTralli, BessemSayadi,FrédéricFaucheux, and SylvaineKerboeuf “Improving QoEand Fairness in HTTP Adaptive Streaming Over LTE Network”, IEEE Trans. on Circuits and Systems for Video Technology, Vol. 26, Issue: 12, pp. 2284 – 2298, Dec. 2016

[39]. Yu-Lin Chient, Kate Ching-Ju Lin, and Ming-Syan Chen, “Machine Learning Based Rate Adaptation with Elastic Feature Selection For Http-Based Streaming”, Proc. of IEEE International Conference on Multimedia and Expo (ICME), Turin, Italy, 29 June-3 July 2015.

[40]. Richard S. Sutton and Andrew G. Barto, “Reinforcement Learning:An Introduction”, MIT PressCambridge, Massachusetts, 2012.

[41]. Virginia Martín, Julián Cabrera, and NarcisoGarcía,“Design, optimization and evaluation of a Q-Learning HTTP Adaptive Video Streaming Client”,IEEE Trans on Consumer Electronics, Vol. 62, No. 4, pp.380-388, Nov. 2016.

[42]. Stefan Winkler, “Video Quality Measurement Standards–Current Status and Trends”, Proc. of 7th International Conference on Information, Communications and Signal Processing (ICICS), Macau, China, 8-10 Dec. 2009.

[43]. ITU-T Recommendation series G, “Transmission systems and media, digital systems and networks”, G.1070, 2012.

[44]. http://www.cse.unsw.edu.au/~cs9417ml/RL1/algorithms.html

[45]. http://jnetpcap.com/