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Design, implementation and testing of QoE-optimization mechanisms for HTTP-based video flows

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Sommario

L'attuale crescita del traffico video in Internet richiede l'uso di una strategia efficiente per distribuire le limitate risorse della rete ai flussi video attivi. La strategia che viene proposta in questo lavoro si basa sull'uso di un Resource Management proxy che sfrutta lo standard ISO/IEC Dynamic Adaptive Streaming over HTTP (DASH) per allocare ad ogni utente, in modo trasparente, una porzione delle risorse disponibili, avendo come obiettivo il mantenimento di un'elevata Quality of Experience (QoE) per tutti gli utenti. Il proxy, inoltre, garantisce un livello di QoE minimo per ogni utente in base alla classe di qualità a cui appartiene.

Sono stati condotti diversi esperimenti per valutare l'effetto di diverse scelte progettuali sulle prestazioni del proxy, in particolare per quanto riguarda l'uso di algoritmi di allocazione delle risorse che sfruttano la relazione tra rate e qualità dei vari flussi video, come nel caso degli algoritmi SSIM Fairness (SF) e Improved SSIM Fairness (ISF), rispetto all'uso di algoritmi che non considerano tale relazione, come nel caso dell'algoritmo Rate Fairness (RF). I risultati sperimentali mostrano che l'uso del Resource Management proxy permette di migliorare in maniera sostanziale la qualità percepita dagli utenti rispetto all'uso della sola logica adattativa gestita indipendentemente da ciascun client, raggiungendo al contempo un'elevata efficienza nell'uso del canale. Inoltre, l'algoritmo ISF si è dimostrato l'algoritmo di Resource Management capace di coniugare i migliori aspetti dei singoli algoritmi analizzati.

Abstract

The current growth of video traffic consumption by Internet users requires the use of an efficient strategy to distribute limited network resources to the active video flows. In this work, we propose the use of a Resource Management proxy that leverages the system model defined by the ISO/IEC Dynamic Adaptive Streaming over HTTP (DASH) standard to transparently allocate a portion of the available resources to each user, while keeping high Quality of Experience (QoE) for all users. The proxy also guarantees a minimum QoE level for each user, depending on the QoE class the user belongs to.

A comprehensive set of experiments has been carried out to evaulate the effect of various design choices on the proxy performance, regarding in particular the use of QoE-aware Resource Management algorithms, namely SSIM Fairness (SF) and Improved SSIM Fairness (ISF), which exploit the relation between rate and quality of each video, against the use of a QoE-agnostic algorithm, namely the Rate Fairness (RF). The experimental results show that the use of Resource Management proxy is able to greatly improve the quality perceived by the user with respect to the use of just an adaptation logic governed independently by each client, plus reaching high efficiency in channel use. Furthermore, ISF proves to be able to conciliate the best aspects of all other Resource Management algorithms.

Contents

Chapter 1

Introduction

In recent years, video consumption by Internet users has grown exponentially [1], resulting in possible network congestion. This happens because the current network infrastructure, especially in the mobile case [2], was not designed to substain such a large amount of video and multimedia traffic and the upgrade of network capacity is complex and costly. To support the current growth of video traffic, which will account for 79% of all IP traffic by 2018 [1], a viable solution is to specifically design a technology for video traffic shaping and Quality of Experience (QoE) management.

In this thesis we design and implement a Resource Management proxy dedicated to the control of the channel resources assigned to video flows, with the aim of keeping the perceived QoE od each user at an acceptable level even in the case of congested channels. To this end, the proxy groups users in various QoE classes and provides different QoE to different classes. This feature allows the use of the Resource Management proxy in commercial streaming services, where *premium* users should be given high QoE even to the detriment of other users. To evaluate the real performance of this solution, it has been compared against the currently available alternatives by means of experimental results.

The rest of the thesis is organized as follows.

Chapter 2 will first explain the relation between video rate and QoE, with a particular focus on the Structural Similarity (SSIM) quality index [3]. Then, it will describe how this relation can be used to design various algorithms dedicated to channel resources allocation, namely the SSIM Fairness (SF) and Improved SSIM Fairness (ISF) [4]. A simulative comparison between these algorithms and a QoE-agnostic algorithm is also presented.

Chapter 3 will be dedicated to the description of the ISO/IEC standard Dynamic Adaptive Streaming over HTTP (DASH) [5], which is a widely supported International Standard for adaptive video streaming over HTTP. The Resource Management proxy will exploit the infrastructure of this standard to provide a transparent resource allocation to DASH video clients.

Chapter 4 will explain the Resource Management proxy workflow and the implementation choices behind it, that will be tested in Chapter 5 under various load conditions. Results reported in Chapter 5 will be compared to those obtained without the use of any centralized resource allocation system. All the comparisons will be held considering two important and, somewhat, contrasting aspects of video consumption experience: the video quality as reported by the SSIM index and the freezing time, which is the time intervals where the playout needs to stop because the playout buffer runs empty and needs to get filled up again. These experiments will allow us to get a clear understanding of pros and cons of each solution, which will be summed up in the final chapter.

Chapter 2

Resource Management and Video Admission Control

The implemented system is based on a group of algorithms to optimally allocate channel resources to video flows. These algorithms, which will be described in Section 2.2, are in turn based on the relation between a given quality metric and the bitrate of the video. This relation, along with the description of the chosen quality metric, will be introduced in Section 2.1.

2.1 Video analysis

Video coding techniques can compress videos to various target bitrates, obtaining different quality levels. To evaluate the quality of experience (QoE) of the compressed videos in an objective way, the *Structural Similarity* (SSIM) index [3] can be used. It measures the degradation of an image with respect to its uncompressed version in terms of perceived variation of structural information. Table 2.1 shows the mappings between SSIM index and *Mean Opinion Score* (MOS) scale, which assesses the subjective perceived video quality.

SSIM	MOS	Quality	Impairment
≥ 0.99	5	Excellent	Imperceptible
$[0.95, 0.99)$	4	Good	Perceptible but not annoying
$[0.88, 0.95)$	3	Fair	Slightly annoying
$[0.5, 0.88)$	2	Poor	Annoying
< 0.5	1	Bad	Very annoying

Table 2.1: Mapping SSIM to Mean Opinion Score

The frame SSIM index calculation is performed by averaging the SSIM metric computed on a rectangular window (usually of size 8×8) that moves pixel by pixel over the entire frame. SSIM index for corresponding windows X and Y of, respectively, the uncompressed and compressed versions of a frame is calculated as follows:

$$SSIM(X,Y) = \frac{(2\mu_X\mu_Y + c_1)(2\sigma_{XY} + c_2)}{(\mu_X^2 + \mu_Y^2 + c_1)(\sigma_X^2 + \sigma_Y^2 + c_2)} \tag{2.1}$$

where μ and σ^2 are the mean and variance of the luminance value in the used windows, while c_1 and c_2 are variables used for numerical stability. The frame metric computed in this way assumes values between 0 and 1, where values 0 and 1 represent the extreme cases of completely different and perfectly identical frames, respectively. The overall SSIM index for a compressed video is then obtained averaging the frame SSIM index over all video frames.

It is of interest to define the *Rate Scaling Factor* (RSF) as

$$\rho = \log(r_v(c)/r_v(1)) \tag{2.2}$$

where $r_v(c)$ is the transmit rate of video v compressed at quality level c, while $r_v(1)$ is the maximum (full quality) rate. For a video coded using the H.264 video compression standard [6], the relation between the video RSF and its SSIM index

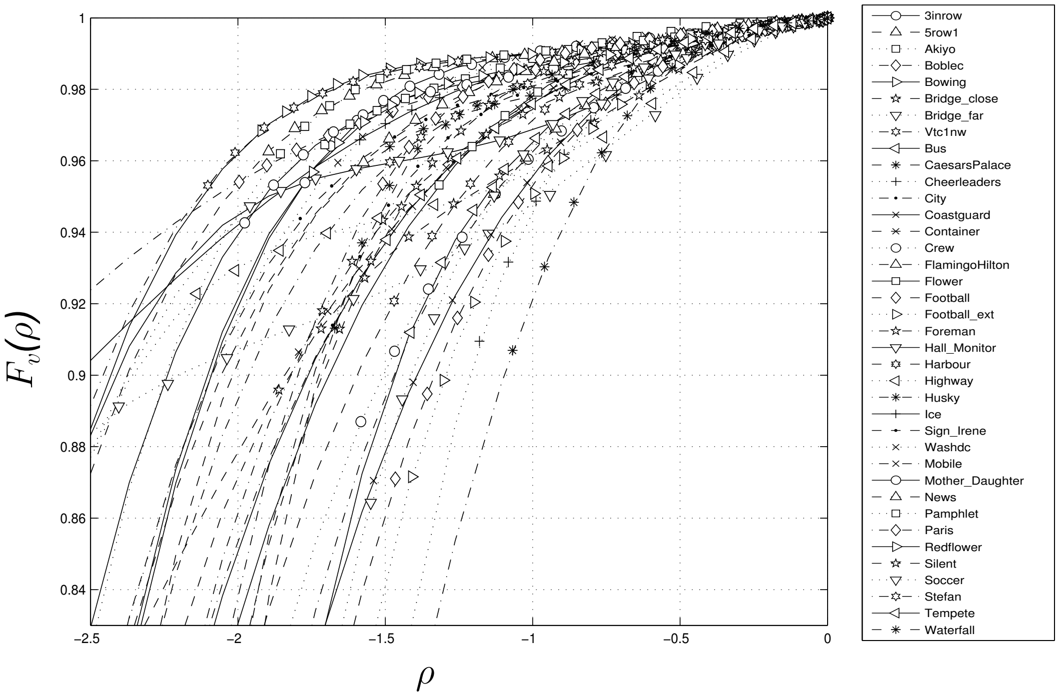


Figure 2.1: SSIM of the different video clips when varying the RSF: markers show empirical values, lines are obtained by the 4-degree polynomial approximation $F_v(\rho)$.

is well approximated by the 4-degree polynomial [7]

$$F_v(\rho) \simeq 1 + a_{v,1}\rho + a_{v,2}\rho^2 + a_{v,3}\rho^3 + a_{v,4}\rho^4 \; . \tag{2.3}$$

This polynomial relation, which characterizes each video, is a continuous function that relates SSIM index and RSF, although H.264 standard entails only a discrete set of quantization levels. For simplicity, in the remaining of this chapter, we will consider the polynomial approximation as exact.

The polynomial coefficients are specific to a single video, so the problem of how to calculate these coefficients arises. In recent years, a technique to get the coefficients starting from the size of frames coded in a GOP has been developed [8]. This technique adopts a machine learning approach to provide a fairly accurate estimate of these polynomial coefficients. This allows the proxy to calculate the coefficients on the fly, without relying on offline processing of the videos. Because of this, it is possible to assume that the polynomial coefficients of each video are known, allowing the resource allocation algorithms to leverage the polynomial relation between RSF and SSIM index.

2.2 RM and VAC algorithms

The objective of RM and VAC algorithms is to distribute the network resources amongst video users in order to guarantee maximum QoE. We consider the network to have a bottleneck link, which can be, for example, the wireless downlink to mobile users or an ADSL connection, shared by all video traffic directed to the users. Users are supposed to be distributed in three QoE classes: bronze, silver and gold. Users in a given class must receive only video flows with SSIM index greater than or equal to a certain SSIM threshold assigned to that class. The SSIM thresholds are called F_1^*, F_2^* and F_3^* for, respectively, bronze, silver and gold class.

When the server receives a request for a new video flow, it computes a new bitrate allocation for all active video flows (including the new request) using the *Resource Management* (RM) algorithms described in the next section. Then, the *Video Admission Control* (VAC) algorithm checks whether the resulting SSIM for each video flow is above the threshold imposed by the QoE class it belongs. In this case, the new video flow is accepted and new rate allocation is enforced. Conversely, if even one flow does not respect the SSIM threshold imposed by its class, then the new video request is blocked (i.e., rejected) and the remaining flows will continue to be served with the previous rate allocation scheme. When a video ends its playback, the server computes a new bitrate allocation for video flows that are still active and applies it without further checks.

2.2.1 RM algorithms

The objective of the RM algorithm is to maximize the SSIM of video flows following a certain allocation strategy, which characterizes the specific algorithm. In this section three different RM algorithms will be described: the *Rate Fairness* (RF), the *SSIM Fairness* (SF) and the *Improved SSIM Fairness* (ISF) [7, 8, 4].

Defining $\Gamma = \{\gamma_v\}$ an allocation vector that assigns to the ith video a portion γ_v of R, it is possible to rewrite the RSF for video v as

$$\tilde{\rho}_v = \log\left(\frac{\gamma_v R}{r_v(1)}\right) . \tag{2.4}$$

Then, the general problem that an RM algorithm needs to solve can be formally described as

$$\Gamma_{\text{opt}} = \underset{\Gamma}{\operatorname{argmax}}\, U(\Gamma, R, \{F_v\}) \quad \text{s.t.} \quad \sum_v \gamma_v \leq 1 \tag{2.5}$$

where $U(\cdot)$ is the utility function considered by the optimization algorithm. Now the three cited RM algorithms will be described in detail.

Rate Fairness (RF)

With this algorithm, resources are distributed to video flows proportionally to their full quality rate (hence the name Rate Fairness). Therefore, the optimal rate allocation is given by

$$\gamma_{\text{opt},v} = \frac{r_v(1)}{\sum_i r_i(1)} . \tag{2.6}$$

The RSF of each video is then $\tilde{\rho} = \log(R/\sum_i r_i(1))$.

SSIM Fairness (SF)

In this case the utility function is

$$U(\Gamma, R, \{F_v\}) = \min_v \left(F_v(\tilde{\rho}_v) - F^*_{q(v)}\right) ; \tag{2.7}$$

where $q(v) \in \{1, 2, 3\}$ is the quality class of the user that has requested video v. In this way, we force every video flow to have the same difference $\alpha = F_v(\tilde{\rho}_v) - F^*_{q(v)}$ between the actual SSIM and the threshold relative to its class, so the utility function can also be written as $U(\Gamma, R, \{F_v\}) = \alpha$. Because of this, the channel allocation Γ depends only on α, so the max-min objective function can also be written as $\mathrm{argmax}_\Gamma\, U(\Gamma, R, \{F_v\}) = \mathrm{argmax}_\alpha\, \alpha$, which is equivalently expressed as

$$\alpha_{\text{opt}} = \max \alpha \ . \tag{2.8}$$

Also, given that the functions $\{F_v\}$ are monotone increasing (and so invertible) in the interval of interest, it is possible to rework the definition of α to obtain

$$\tilde{\rho}_v = F_v^{-1}\left(\alpha + F^*_{q(v)}\right) \ . \tag{2.9}$$

It is also possible to rework the definition of RSF to get

$$\gamma_v = \frac{1}{R}\, r_v(1)\, 10^{\tilde{\rho}_v} \ . \tag{2.10}$$

Consequently, the constraint can be rewritten so that it depends only on α, as

$$\sum_v \frac{1}{R} r_v(1) 10^{F_v^{-1}\left(\alpha + F^*_{q(v)}\right)} \leq 1 \ . \tag{2.11}$$

The maximum α that satisfies (2.11) inequality is then α_{opt}.

Given α_{opt}, the optimal allocation $\Gamma_{\text{opt}} = \{\gamma_v\}$ can then be retrieved using equations (2.9) and (2.10). This result leads to a simple solution solution of the problem, because the optimal value of α can be obtained finding the zero of monotone function

$$F(\alpha) = \sum_v r_v(1) 10^{F_v^{-1}(\alpha + F^*_{q(v)})} - R \tag{2.12}$$

for $0 \leq \alpha \leq \max_v \left(1 - F^*_{q(v)}\right)$ (e.g., by bisection method). The extreme cases where the constraint is not satisfied for $\alpha = 0$ (which means the problem does not admit solution and the new request must be rejected) or where the constraint is satisfied for $\alpha = \max_v \left(1 - F^*_{q(v)}\right)$ (which means the new request is accepted and every video can be trasmitted at its full quality) must be treated separately. Of course, given that with this approach the SSIM index $\alpha + F^*_{q(v)}$ could exceed 1 during the intermediate steps of the algorithm, the value of $F_v(\cdot)$ and $\tilde{\rho}_v$ must be limited to, respectively, 1 and 0.

Improved SSIM Fairness (ISF)

Similarly to the SF case, we now define the utility function as

$$U(\Gamma, R, \{F_v\}) = \min_v \frac{F_v(\tilde{\rho}_v) - F^*_{q(v)}}{1 - F_v(\tilde{\rho}_v)} \ . \tag{2.13}$$

In this way, we force each video flow to have a rate such that $\alpha = \frac{F_v(\tilde{\rho}_v) - F^*_{q(v)}}{1 - F_v(\tilde{\rho}_v)}$ is the same for all video flows. As in the previous case, the utility function can also be written as $U(\Gamma, R, \{F_v\}) = \alpha$ and the max-min objective function becomes again

$$\alpha_{\text{opt}} = \max \alpha \ . \tag{2.14}$$

Again, given that the functions $\{F_v\}$ are invertible in the interval of interest, it is possible to rework the definition of α to obtain

$$\tilde{\rho}_v = F_v^{-1}\left(\frac{F^*_{q(v)} + \alpha}{1 + \alpha}\right) \ ; \tag{2.15}$$

using the results obtained in the previous case, the constraint can be rewritten as

$$\sum_v \frac{1}{R} r_v(1) 10^{F_v^{-1}\left(\frac{F^*_{q(v)} + \alpha}{1 + \alpha}\right)} \leq 1 \ . \tag{2.16}$$

Once again, α_{opt} is the maximum α that satisfies (2.16) inequality.

Given α_{opt}, the optimal allocation $\Gamma_{\mathrm{opt}} = \{\gamma_v\}$ can then be retrieved using equations (2.15) and (2.10). This result leads to a solution similar to that found in the SF case, which consists in finding the zero of the monotone function

$$F(\alpha) = \sum_v r_v(1) 10^{F_v^{-1}\left(\frac{F^*_{q(v)}+\alpha}{1+\alpha}\right)} - R \; , \tag{2.17}$$

for $0 \leq \alpha < +\infty$. The extreme case where the constraint is not satisfied for $\alpha = 0$ (which means the problem does not admit solution and the new request must be rejected) must again be treated separately.

2.2.2 Simulative comparison between the RM algorithms

To appreciate the pros and cons of each algorithm, we have simulated their behaviour in a common reference scenario. The trasmission scenario comprises a video server, a large number of users and a congested link of bitrate R between the users and the video server. The congested link is shared by a number of video clients. In the rest of the thesis it is assumed that the time scale of the channel capacity fluctuations due, for instance, to fading phenomena, is much smaller than the time scale of the video service, so that VAC and RM algorithms can work with the time-averaged value of the channel capacity.

Users are uniformly distributed in three QoE classes: bronze, silver and gold. Users in a given class must receive only video flows with SSIM index greater than or equal to the SSIM threshold for that class. The SSIM thresholds are $F^*_1 = 0.9$, $F^*_2 = 0.95$ and $F^*_3 = 0.98$ for bronze, silver and gold class, respectively, corresponding to an average MOS of 3, 4 and 5 (Table 2.1). Video requests are generated according to a Poisson process of overall rate $\lambda_a = 0.1$ requests/s. Video duration, instead, follows an exponential distribution with mean $1/\lambda_d = 100$ s. In this way, the offered traffic of full quality videos is $G = E[r_v(1)]\lambda_a/\lambda_d$, where $E[r_v(1)]$ is the average bitrate of the uncompressed videos in the pool. Moreover, assuming infinite link capacity, the average number of active video flows would be $N_\infty = \lambda_a/\lambda_d = 10$, while the average number of active video flows per class would be $N_\infty/3$.

In the following, the algorithms are compared in terms of average SSIM values for active flows, average number of active flows, blocking probability of a video request and amount of unallocated channel capacity.

Looking at Figure 2.2, we can see that the average SSIM per class is higher than the respective SSIM threshold in all cases, as per the VAC objective. However, the three algorithms behave differently with regards to this aspect: in fact, whilst SF and ISF exploit the different SSIM thresholds for various classes and they keep, whenever the channel is highly crowded, the SSIM index of video flows near their threshold, RF divides the channel rate without considering the impact on the SSIM index, leading to a less pronounced average SSIM difference between various classes, as the graph shows. In fact, being RM QoE-agnostic, the only cause for the gap between SSIM classes in RF curve is the behaviour of the VAC algorithm, which applies the QoE grouping by accepting and rejecting the video flows.

It is worth noting that SF experiences a slight, yet noticeable, decrease of the average quality for bronze and silver flows for increasing channel capacity, until a value of R/G equal to 0.1 is reached. This is followed by a pronounced increase in quality, common to all algorithms, when $R/G > 0.1$. The reason for this behaviour is that, when R/G is small, an increasing channel capacity allows the algorithm to accommodate an increasing number of video flows in the channel even at the expense of reducing quality of active video flows. When the value of R/G is larger than 0.1, however, the channel capacity is sufficient to admit most of video requests, at least using SF (Figure 2.3), and a higher channel capacity yields an increased quality of active users.

Comparing the effects that RM algorithms have on the average SSIM for different classes, we can see that gold users benefit from a QoE-aware admission mechanism whereas silver and bronze flows reach a higher quality when the RF

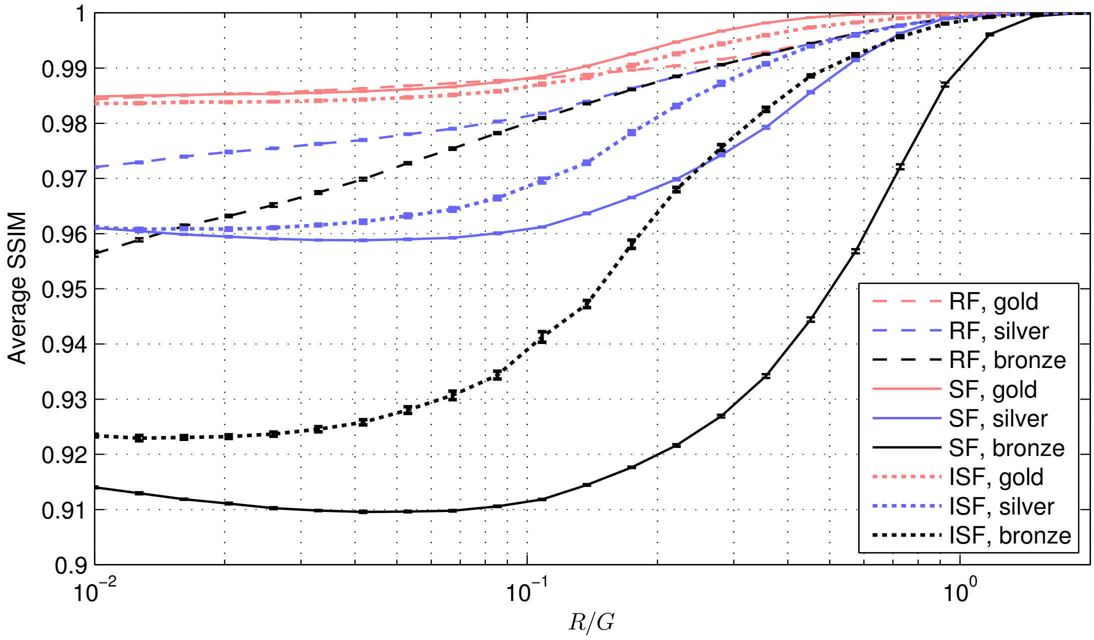


Figure 2.2: Average SSIM for active video flows, with 95% confidence intervals

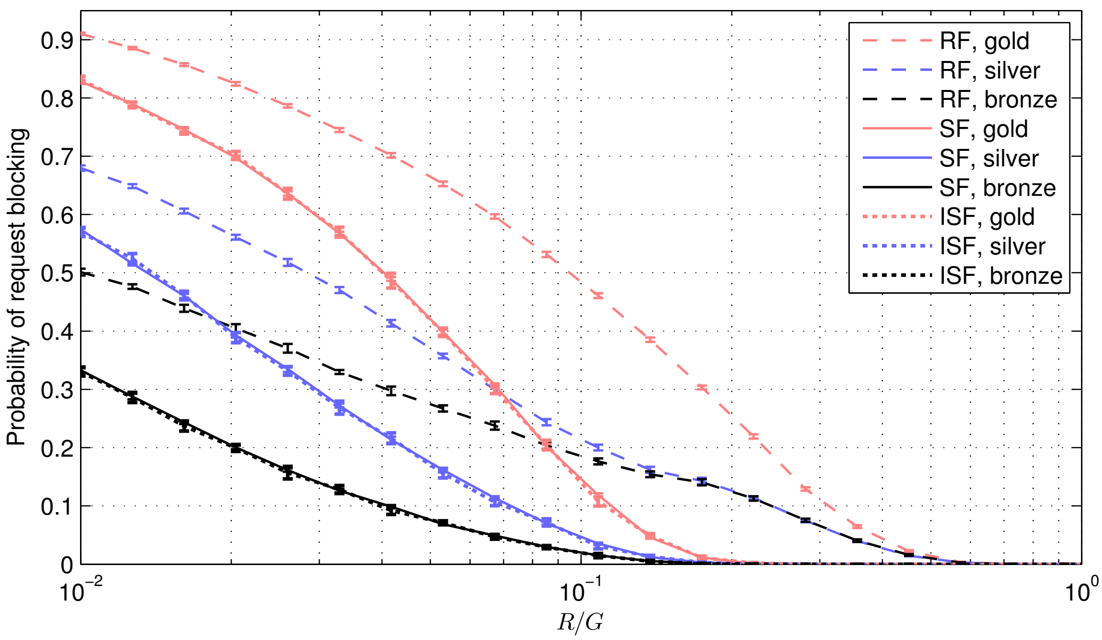


Figure 2.3: Video block probability, with 95% confidence intervals

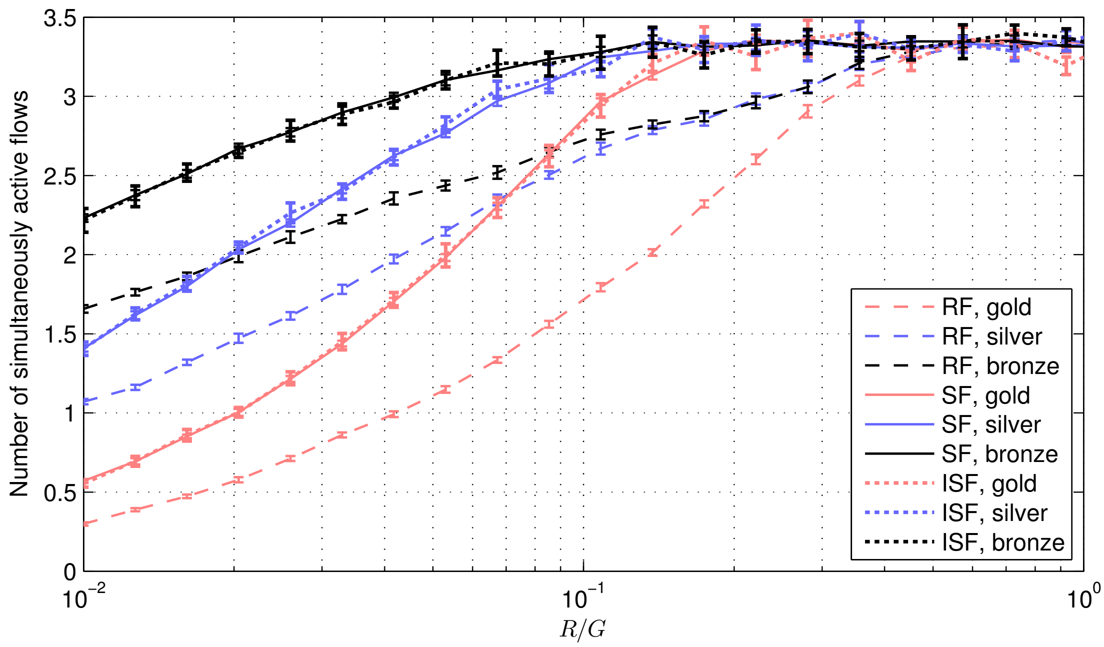


Figure 2.4: Average number of simultaneously active video flows, with 95% confidence intervals

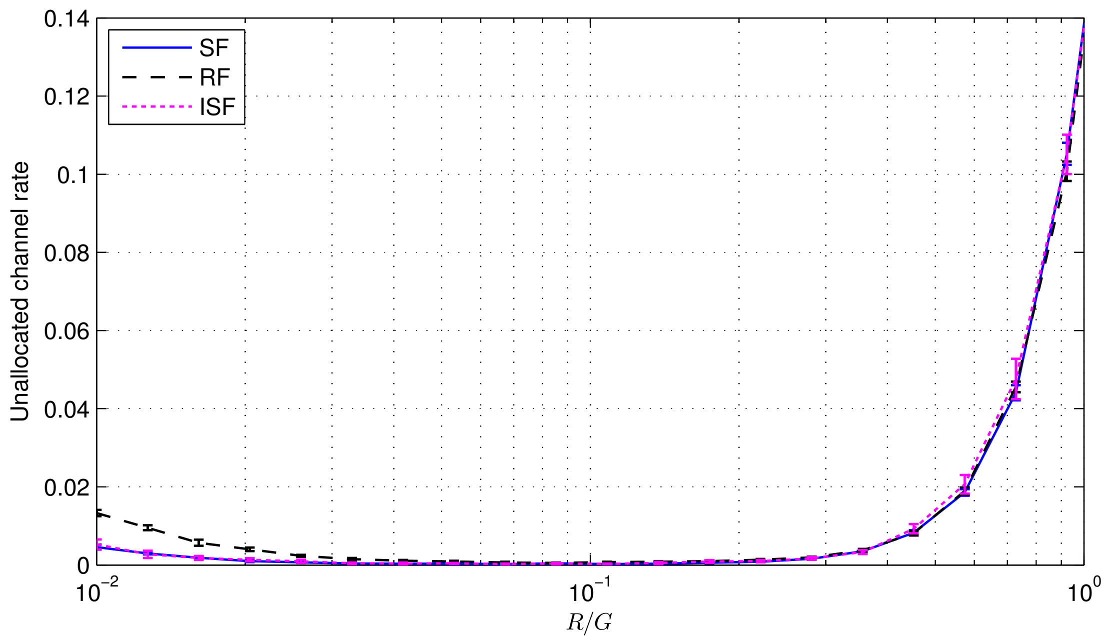


Figure 2.5: Fraction of the channel rate left unused, with 95% confidence intervals

scheme is being used. The reason of these results is revealed by the curves shown in Figures 2.3 and 2.4, where the block probability and the number of active flows for each quality class using the three RM algorithms are reported. We can observe, in fact, that in the considered channel rate range, SF and ISF are able to pack more video flows in the channel and, consequently, the block probability is smaller for SF and ISF than for RF. This is because RF does not take into account the relationship between SSIM index and video rate, hence it cannot reduce the quality of videos with a SSIM much greater than the class threshold in favor of videos that do not meet the minimum QoE condition. As a consequence, the VAC algorithm will accept more video requests with SF and ISF than with RF, though the average quality of the accepted videos will be, on average, lower than that achieved with RF.

To mitigate this problem, ISF tries to reduce, with respect to the SF allocation, the rate allocated to gold flows in favor of silver and bronze flows. This allows a great increase in SSIM values for silver and bronze video flows, at the cost of an insignificant reduction in quality of gold flows. This is because typical RSF-SSIM curves (Figure 2.1) are almost flat for values of RSF near 0, so that a small rate decrease for such video flows does not impact in a significant way the video quality.

When comparing the values of average number of active flows for various classes of videos using the same RM algorithm, it can be seen that the highest number of flows are of bronze class, followed by silver class and then gold class, for all RM algorithms. This is because bronze flows have lower requirements in terms of minimum SSIM value (and so minimum bitrate), allowing them to be accepted even when the channel is particularly crowded. Gold video flows require, instead, higher resources, which could be not available when the channel is already used by an high number of flows. Analogously, the probability of rejection per class shows the same situation, where, with any of the considered algorithms, flows belonging to the gold class are the most likely to be rejected, while bronze video flows have the lowest probability of rejection. Of course, it is possible to encompass a class downgrade mechanism to avoid blocking, but this variant has not been considered.

In Figure 2.5 the fraction of channel bandwidth that is left unused by RF, SF and ISF is reported. All algorithms have an U-shaped behaviour as a function of the ratio R/G. When the aggregate offered traffic for full quality videos is much higher than the channel rate, namely $R/G < 0.1$, it is possible to note that the RF leaves more unallocated capacity or, equivalently, it uses less resources than SF and ISF. This happens because RF, considering only the nominal video rate for resource allocation, will not decrease the rate of videos that are well above the minimum quality threshold in order to *make space* for additional videos, which will hence be blocked by the VAC algorithm despite some resources remaining unused.

For $R/G > 0.1$, instead, the fraction of unused capacity by all algorithms grows quite rapidly. This happens because the channel rate is comparable with respect to the sum of full quality rate of all active video flows, so, when the offered traffic is lower than its average value because of the fluctuations of the video request process, the channel resources are sufficient to transmit all the active video flows at full quality, thus leaving some unused resources. This is also confirmed from Figure 2.2, where we can see that, in this region, the average video quality grows as quickly as the fraction of unallocated channel bandwidth.

As a general remark, we can see that RF manages to get better average SSIM values with respect to SF, while, on the contrary, SF allocates videos in such a way to allow a bigger number of simultaneously active flows with respect to RF. ISF, instead, manages to get the overall best behaviour amongst the analyzed algorithms, providing average SSIM values near to the ones obtained using RF, while keeping video rejection probabilities, average number of active flows and fraction of unallocated channel rate essentially identical to the ones obtained using SF.

Chapter 3

Adaptive bitrate streaming

3.1 Introduction to adaptive streaming

Adaptive bitrate streaming is a technique that enables optimum multimedia streaming over telecommunication networks across a wide range of devices and connection speeds. Its main peculiarity is the ability to detect and monitor user's available bandwidth and CPU capacity to adapt in real-time the video flow bit rate accordingly.

In particular, adaptive streaming is a method of multimedia streaming where the source content is encoded at multiple bit rates, then each coded content is splitted in segments with duration of a few seconds. Retrieving a manifest file, the client can be aware of the presence of these multiple encoded versions and the location of the various segments. Now the client is able to retrieve the segments to playback the whole multimedia content choosing, for each temporal interval, the segment relative to the desired quality level. This choice can be made in an autonomous way by the client, based on available network bandwidth and on CPU capacity of user's device.

A key difference between streaming technologies is the type of used streaming protocol. While in the past the most adopted solutions used protocols like RTP with RTSP, nowadays adaptive streaming technologies are almost exclusively based on HTTP. This allows to have various advantages with respect to other solutions, in particular:

- it allows the reuse of existing server infrastructure, without the need to have dedicated servers as in the case for RTP streaming;
- it is firewall-friendly, because with HTTP protocol the video streaming packets are generally not blocked by firewalls;
- it can exploit existing HTTP cache infrastructure to offer video segments from a nearer location to the user with respect to the original server, enabling faster video delivery.

3.2 Introduction to MPEG-DASH

MPEG-DASH (*Dynamic Adaptive Streaming over HTTP*) [5] is an ISO standard developed by the *Motion Picture Experts Group* (MPEG) that defines an adaptive bitrate streaming technique based on HTTP.

DASH development started in 2010, evolving into a Draft International Standard in January 2011 and an International Standard in November 2011. The MPEG-DASH standard, first published in April 2012 as ISO/IEC 23009-1, has been updated on July 2013, incorporating some amendments and corrigenda.

MPEG-DASH is the first HTTP-based adaptive streaming solution that arose at the level of international standard. It was preceded by similar, but proprietary, adaptive streaming technologies, like Adobe's *HTTP Dynamic Streaming*, Apple's *HTTP Live Streaming* [9] and Microsoft's *Smooth Streaming*. The objective for MPEG-DASH was to replace those technologies by incorporating their strong points into a widely implemented and vendor-independent standard, in order to enable the use of a single technology for multimedia streaming on all platforms. To reach this objective, the standardization group worked together with the most important stakeholders, like Adobe, Apple, Microsoft, Netflix and Qualcomm, and with other standardization bodies, in particular with 3GPP, that was developing a similar technology, called *Adaptive HTTP Streaming* (AHS) [10].

Nowadays the standard is implemented in various products and gained traction as the only available technology allowing adaptive bitrate streaming on devices from different vendors.

3.3 DASH data model

MPEG-DASH defines a media content delivery model where the control is primarily client-side. In fact, clients may request data, using HTTP protocol, from standard web servers that have no DASH-specific capabilities. Because of that, the DASH standard focalizes on data formats used in data exchanges and not on client and server procedures.

The set of deliverable encoded versions of media content, along with their description, forms a *Media Presentation.* A DASH Media Presentation is described by an XML manifest file called *Media Presentation Description* (MPD) [5].

Media content is composed by one or more contiguous *periods* in time. These periods could represent parts or episodes of a main program, interleaved with inserted advertisement periods. The set of the available coded versions of media content must be consistent throughout a period, i.e., the available languages, subtitles, bitrates, etc. can not change within a period.

In a period, material is divided in *adaptation sets.* An adaptation set represents a set of coded version of a media component. For example, there could be an adaptation set for the main video component and a separate one for the main audio component. Other components, like subtitles or other audio tracks, could have a dedicate adaptation set each. Those media components could also be provided in multiplexed form. In this case, interchangeable versions of the *multiplex* may be described with a single adaptation set. An example for this case is an adaptation

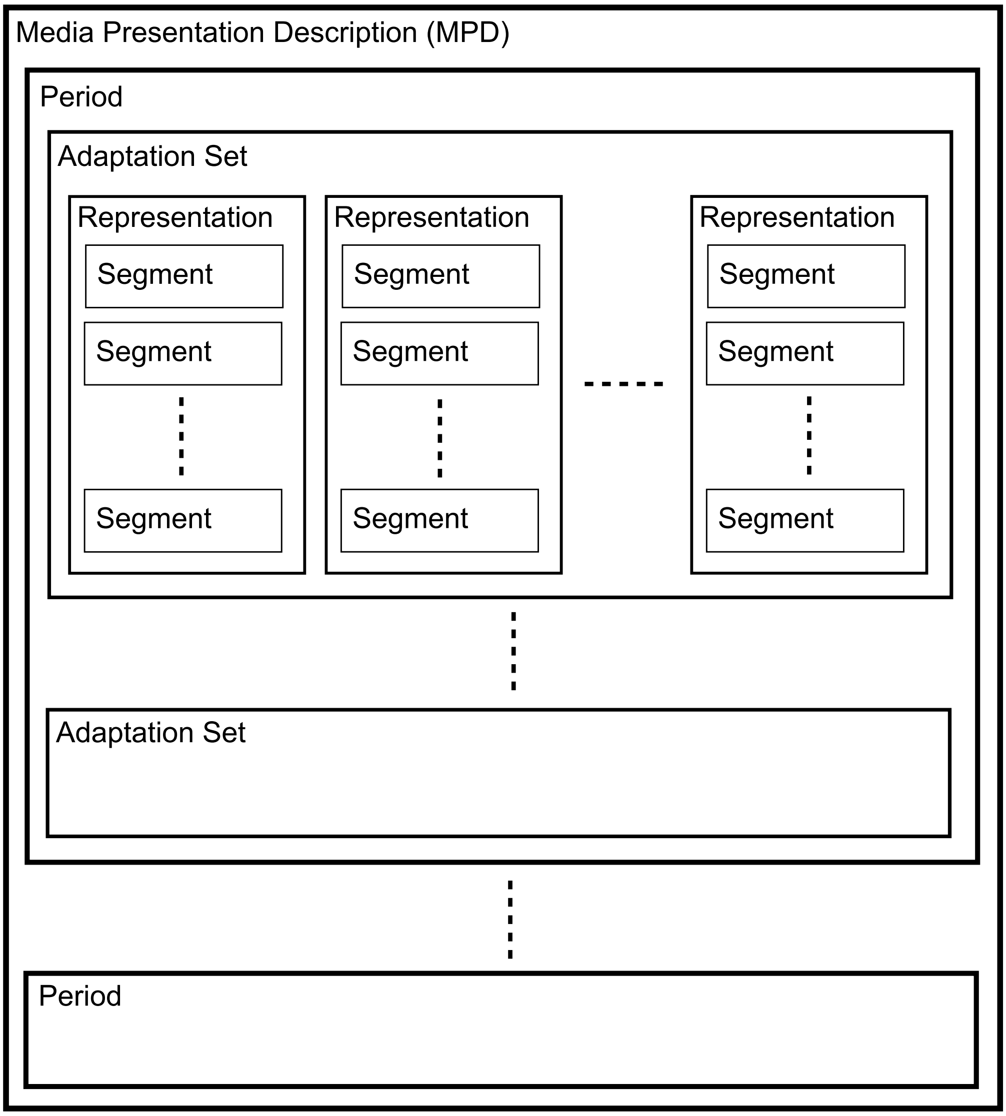


Figure 3.1: DASH data model

set containing both the main audio and main video for a period, with additional components being provided in additional adaptation sets.

An adaptation set contains a set of *representations*. A representation describes a deliverable encoded version of one or multiple media content components. Each representation in an adaptation set is sufficient to render the contained media components, but, grouping together several representations in a single adaptation set, the Media Presentation author states that those representations represent perceptually equivalent contents. This means that clients can dynamically swicth between representations in an adaptation set in order to adapt to network conditions or other factors. Switching refers to the presentation of decoded data of one representation up to a certain time instant, and the presentation of decoded data of another representation from that instant onwards. If both representations are included in the same adaptation set, and the client switches properly, the media playout is perceived seamless across the switch.

Within a representation, the content may be divided in time into *segments*. In order to access a segment, an URL is provided for each segment.

Segments description in the MPD manifest file could be expressed in one of the following ways:

- *SegmentBase*: this description in used when only a single media segment is provided per representation. In this case, an URL (with an optional byte range) is reported for each representation, which references the file containing the segment for the considered representation. An example exploiting the possibility to make HTTP/1.1 byte-range requests follows:

```
<Representation id="1" mimeType="video/mp4" codecs="avc1.4d401f"
  width="1280" height="720" bandwidth="2073921">
  <BaseURL>car-20120827-88.mp4</BaseURL>
  <SegmentBase indexRange="708-1183">
    <Initialization range="0-707" />
  </SegmentBase>
</Representation>
```

- *SegmentList*: in this case the description of each representation includes a list of segment URLs, one for each segment of the considered representation. Each segment URL is composed by a file location and, optionally, a byte range, allowing to make byte-range requests according to HTTP/1.1 specification. A self-explanatory example for this case follows:

```
<Representation id="1" mimeType="video/mp4" codecs="avc1.640016"
  width="352" height="288" bandwidth="6772590">
  <BaseURL>akiyo0_dashinit.mp4</BaseURL>
  <SegmentList timescale="1200000" duration="5952000">
    <Initialization range="0-865"/>
    <SegmentURL mediaRange="866-4205261" indexRange="866-969"/>
    <SegmentURL mediaRange="4205262-8393927" indexRange="4205262-4205365"/>
    <SegmentURL mediaRange="8393928-10158885" indexRange="8393928-8393995"/>
  </SegmentList>
</Representation>
```

- *SegmentTemplate*: in this case, the list of segment URLs is expressed by a template and some replacement rules that allows to swap special identifiers with appropriate dynamic values assigned to segments. The simplest case is when the template is made by a fixed part and an index that assumes increasing values for successive segments. In this way it's possible to use DASH technology for streaming of live media content, where segments are delivered to clients while successive ones are still being generated, making impossible the creation of a segment URLs list beforehand. A simple example of this case, where `$Number$` is the placeholder for the segment number, could be:

```
<Representation id="1" mimeType="video/mp4" codecs="avc1.640016"
  width="352" height="288" bandwidth="10059517">
  <SegmentTemplate timescale="1200000" media="seg_bowing0$Number$.m4s"
  startNumber="1" duration="2304000" initialization="seg_bowing0init.mp4"/>
</Representation>
```

```xml
<?xml version="1.0"?>
<MPD xmlns="urn:mpeg:dash:schema:mpd:2011" minBufferTime="PT1.500000S" type="static"
   mediaPresentationDuration="PT0H0M12.00S" profiles="urn:mpeg:dash:profile:full:2011">

   <ProgramInformation> <Title>akiyo0_dash.mpd</Title> </ProgramInformation>

   <Period duration="PT0H0M12.00S">
      <AdaptationSet segmentAlignment="true" maxWidth="352"
         maxHeight="288" maxFrameRate="25" par="352:288">

         <Representation id="1" mimeType="video/mp4" codecs="avc1.640016" width="352"
            height="288" frameRate="25" sar="1:1" startWithSAP="1" bandwidth="6772590">
            <BaseURL>akiyo0_dashinit.mp4</BaseURL>
            <SegmentList timescale="1200000" duration="5952000">
               <Initialization range="0-865"/>
               <SegmentURL mediaRange="866-4205261" indexRange="866-969"/>
               <SegmentURL mediaRange="4205262-8393927" indexRange="4205262-4205365"/>
               <SegmentURL mediaRange="8393928-10158885" indexRange="8393928-8393995"/>
            </SegmentList>
         </Representation>

         <Representation id="2" mimeType="video/mp4" codecs="avc1.640016" width="352"
            height="288" frameRate="25" sar="1:1" startWithSAP="1" bandwidth="5973738">
            <BaseURL>akiyo2_dashinit.mp4</BaseURL>
            <SegmentList timescale="1200000" duration="5952000">
               <Initialization range="0-865"/>
               <SegmentURL mediaRange="866-3709849" indexRange="866-969"/>
               <SegmentURL mediaRange="3709850-7403297" indexRange="3709850-3709953"/>
               <SegmentURL mediaRange="7403298-8960607" indexRange="7403298-7403365"/>
            </SegmentList>
         </Representation>

         <Representation id="3" mimeType="video/mp4" codecs="avc1.640016" width="352"
            height="288" frameRate="25" sar="1:1" startWithSAP="1" bandwidth="5184079">
            <BaseURL>akiyo4_dashinit.mp4</BaseURL>
            <SegmentList timescale="1200000" duration="5952000">
               <Initialization range="0-865"/>
               <SegmentURL mediaRange="866-3220504" indexRange="866-969"/>
               <SegmentURL mediaRange="3220505-6425239" indexRange="3220505-3220608"/>
               <SegmentURL mediaRange="6425240-7776118" indexRange="6425240-6425307"/>
            </SegmentList>
         </Representation>

      </AdaptationSet>
   </Period>
</MPD>
```

Figure 3.2: Example of an MPD manifest file

3.4 Typical DASH client operation

The typical DASH client procedure to retrieve and render a media stream consists of the following steps:

1. the client retrieves the MPD manifest file from the server and parses it to be aware of all available media components and their representations;

2. the retrieval of the media starts with the download of first segments relative to the desired media components. Usually, the low bitrate version of first segments are chosen, because of the unknown network conditions. In this way, it is also possible to get a faster start of video playout. MPD manifest may also indicate the necessity to retrieve an initialization segment, containing information needed to initialize the media engines for enabling playout of the media segments. If this is not the case, segments are said to be self-initializing, because each of them contains all the necessary information for its decoding.

3. The client estimates network conditions from metrics calculated from previous segments download. These metrics will be helpful in chosing the bitrate of the next media segments to retrieve.

4. Successive segments are retrieved using the metrics calculated in the preceding step. In case of not self-initializing segments, if the new segment belongs to a different Representation with respect to the previous one, the initialization segment for that Representation must be retrieved in order to correctly decode the new segment.

5. Steps 3-4 are repeated until all desired media components are completely retrieved.

3.5 Additional DASH features

DASH technology provides additional features, such as:

- being codec independent, it works with H.264, WebM and other codecs, allowing this technology to be future-proof and adaptable to new codec that will be developed;
- the possibility to support all encryption schemes and DRM techniques specified in ISO/IEC 23001-7 standard enables its use in commercial streaming services;
- it allows for dynamic ads insertion, useful again for commercial streaming services;
- it entails special features to support live streaming, like the possibility to fragment the MPD manifest and download each fragment separately (used to update the manifest with new information that become available after the stream start).

Chapter 4

Resource Management proxy

In this work, we propose the use of a transparent *Resource Management proxy* between the clients and the video server. The purpose of the proxy is to intercept segment requests from clients and redirect them to enforce a resource allocation according to one of the algorithms seen in Section 2.2.1. The use of a transparent proxy allows us to not be tied to the support of a dedicated protocol by the clients and the server. The proxy server is based on mitmproxy [11], an SSL-capable man-in-the-middle proxy for HTTP. This software is able to act as a transparent proxy, thus not requiring any special client or server configuration. In fact, the key property of the RM proxy is to be completely transparent to both the client and the video server. Software of the RM proxy has been written using Python and C, through the use of Cython compiler [12], and employs the scientific libraries NumPy [13] and SciPy [14] to avoid any delay in communications introduced by the proxy processing.

The RM proxy has to be placed between the DASH clients and the HTTP servers, in such a way to intercept every request from clients to servers and every related response. Also, the proxy must know the rate of the channel bottleneck between client and server.

The operations that the proxy performs are different based on the type of intercepted message. In particular, there are three cases: an MPD request from a client, a media request from a client, a media response from the server. Other messages are simply forwarded without further processing. Now the three aforementioned cases will be discussed.

MPD request from a client

In this case a client requests an MPD manifest from the server. The proxy considers this request as the start of a new flow, so it retrieves itself the manifest file, parses it and saves the information contained in it, in particular the set of available representations, along with their bandwidth requirement, and the set of segment URLs for each representation. Note that the bitrate of full quality version of the video can also be obtained from these information, picking the maximum bitrate between all representations. Information allowing the identification of the requesting client, like its IP address, are also also stored and associated with this video flow.

Then, the proxy must obtain the polynomial coefficients indicating the relationship between SSIM index and Rate Scaling Factor. As mentioned in the previous chapters, these coefficients could be obtained directly by the server or estimated through a machine learning approach [8]. In the first case, an appropriate server request must be sent and the response must be parsed to retrieve the coefficients. In the second case, the coefficients have to be estimated with the use of a video segment. There are two possible options to retrieve the segment:

- Immediately retrieve a video segment from the server. The drawback here comes from the need, for the server, to support a dedicated protocol. The advantage is that the coefficients are immediately available for use in the optimization routine.

- Wait to get a response from the server to the client holding a media segment. This does not require the support of a dedicated protocol by the server, but the first segment can not be delivered with the optimal quality, given that at the time of its request the polynomial coefficients will be unknown and will be necessary to use fictional coefficients for optimization purposes.

The quality class of the video flow can, instead, be retrieved based on a rule set in the proxy, the simplest case being three lists of client IP addresses, one for each class, to be stored in a file or a database.

Now the proxy has all the necessary information to run the optimization routine. The output of this routine consists in a flag, indicating if the video flow request is accepted into the system or not, and, in the affirmative case, a list of rates, one for each active video flow.

If the video flow is not accepted, the MPD request is redirected to a special MPD file, containing the description of a short highly compressed video that informs the user about the momentary unavailability of network resources to deliver the requested video.

On the contrary, if the video request is accepted, the new resource allocation is stored and the MPD request is forwarded to the video server. In this case, a timer is also attached to the video flow. If the timer expires, the associated video flow will be considered inactive and a timeout routine will remove it from the list of active flows, redistributing its resources to the other flows.

Media request from a client

When the proxy intercepts a request for a media segment from a client, it needs to know the video flow it belongs to. To this end, it matches the information provided in the HTTP request to the ones stored for the active video flows. The proxy also searches the requested URL, with the optional byte range, within the sets of segment URLs of the selected video flow. In this way, the proxy knows the video flow the request belongs to and, additionally, which time interval of the video clip the client requested. The proxy is then able to build up a pair formed by a representation index and a segment index, where the segment index indicates which time interval the client requested, as retrieved in the previous step, while the representation index is relative to the representation that best matches the optimum bitrate allocation for the given flow. There are two possible ways to choose this optimum representation: the first is to choose the representation with the most similar bandwidth to the optimal one, the second is to choose the representation with the highest bandwidth between the ones with a bandwidth smaller than the optimum. In Section 5.1 the two options will be compared, coming to the conclusion that, even if the first option allows a better channel exploitation, it will cause, with a significant probability, the sum of bitrates allocated to video flows to exceed the available channel rate, causing playout buffer underflows and, consequently, video freezing phenomena at clients. With the appropriate indices pair set up, the proxy is then able to search, through the list of segment URLs, the URL where the request needs to be redirected. The last step, before the request forwarding, is to check if the request is relative to a last segment of the video, in one of its representation. If this is the case, the flow is marked for removal after the reponse will be transmitted. In every case, the timer associated to the video flow is reset. The headers of the request are then rewritten to apply the redirection to the correct segment. As a last step, the request is forwarded to the media server.

Media response from the server

When the proxy receives a media response from the server, it checks if the associated flow is marked for removal. If it is, it forwards the request to the client and then, at the end of the transmission, it removes the flow from the list of active ones and runs the RM algorithm to redistribute the freed resources to the other active flows. It is worth noting that the VAC algorithm needs not to be invoked, because each video will get equal or more resources than it had before, consequently its quality level can not decrease. If the flow is not marked for removal, the media response is simply forwarded to the client.

Chapter 5

Experimental results

A number of experiments have been carried on to evaluate the RM proxy performance. The setting (Figure 5.1) is composed by a video server connected through a high speed link to the RM proxy, which is, in turn, connected to a router through a low speed link of rate R, which is the network bottleneck. The router is then connected, through a switch, to the clients. In these experiments all links uses IEEE 802.3 100BASE-TX standard technology with a maximum rate of 100 Mbit/s. The rate of the bottleneck has been throttled using the netem network emulator available in the Linux kernel. The server runs Debian 7.6 Linux distribution and uses Apache HTTP server to provide the functionality of a DASH video server. The RM proxy runs on Ubuntu 14.04 LTS Linux distribution with Python 2.6, while the router and the clients all run Debian 7.6 Linux distribution. Clients use the Google Chrome 37 browser to run the DASH Reference Player *dash.js*, devel-

Video	Length	Full quality bitrate
paris	42.6 s	12041 kbit/s
coastguard	12 s	14910 kbit/s
football	3.6 s	14296 kbit/s
bowing	12 s	10060 kbit/s

Table 5.1: Video characteristics

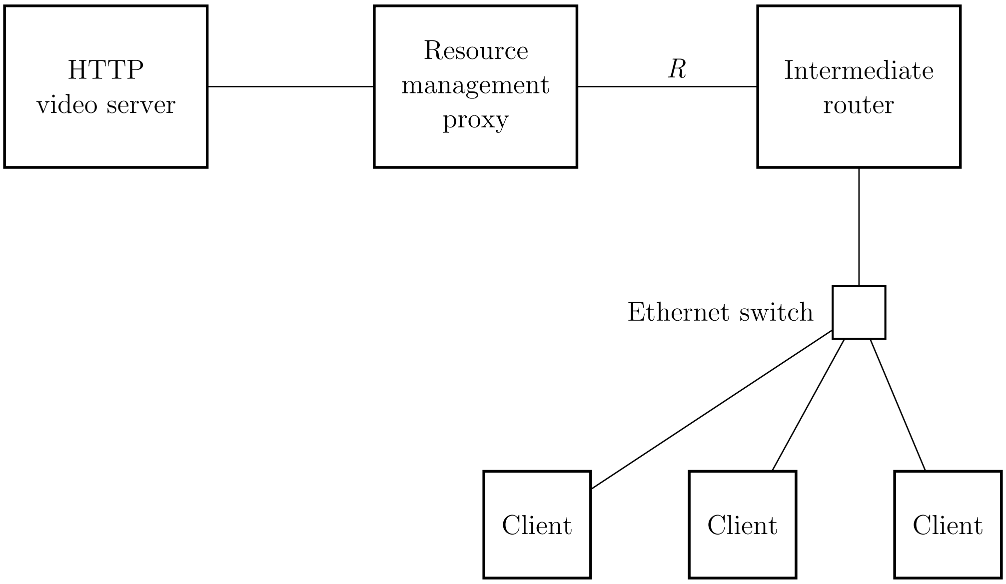


Figure 5.1: Experimental setup.

oped by the DASH Industry Forum. The reference player works in any HTML5 browser which supports the Media Source Extensions [15] and Encrypted Media Extensions [16].

The esperiments have been carried out using videos from standard reference sets[1]. Characteristics of the videos are described in Table 5.1

The next section will describe the results obtained by experimentation.

5.1 Impact of discrete quantization levels

As explained in Section 2.1, in this work we assume continuous rate adaptation logic, i.e., we suppose the video rate can vary in a continuous way. Actually, the H.264 standard defines only a finite set of quantization levels, so that the rate r provided by the RM algorithm needs to be mapped in one of the rates available for each video. Two possibilities will be analyzed.

[1]Video traces can be found in [17], ftp://132.163.67.115/MM/cif

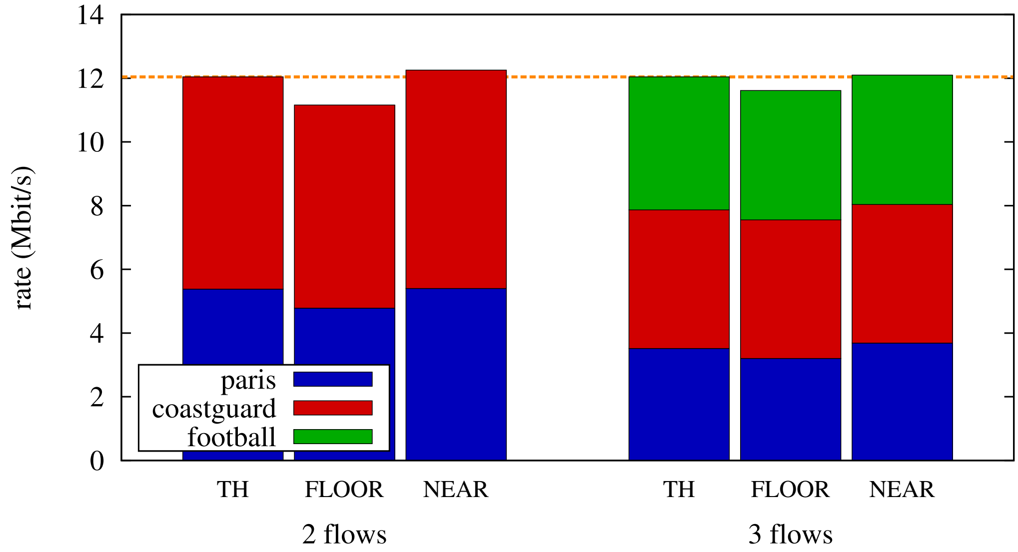
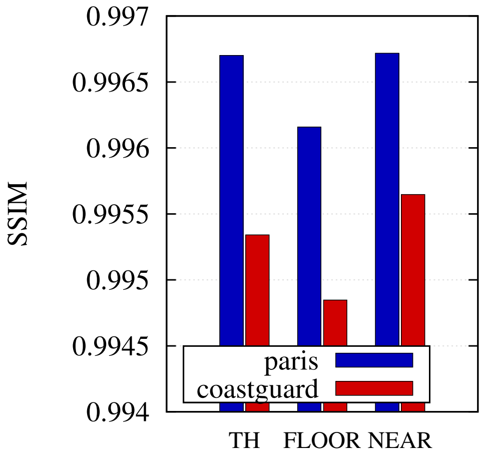
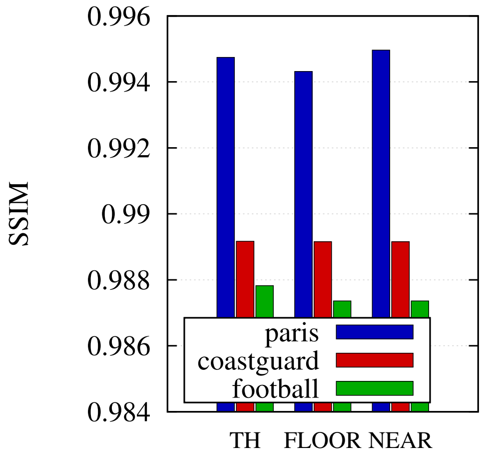


Figure 5.2: Rate assigned to each video flow using RF. TH is the output of the RM algorithm, while FLOOR and NEAR are the assignments using the corresponding strategy. The dashed line represents the bottleneck rate.



(a) 2 flows



(b) 3 flows

Figure 5.3: Resulting SSIM index of video flows using RF. TH is given by the output of the RM algorithm, FLOOR and NEAR refer to the corresponding strategy.

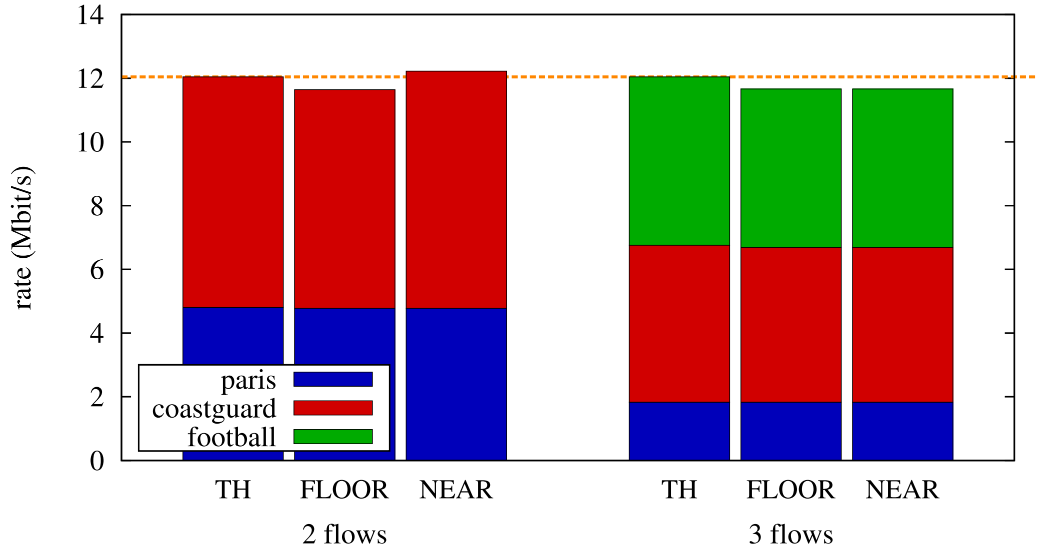
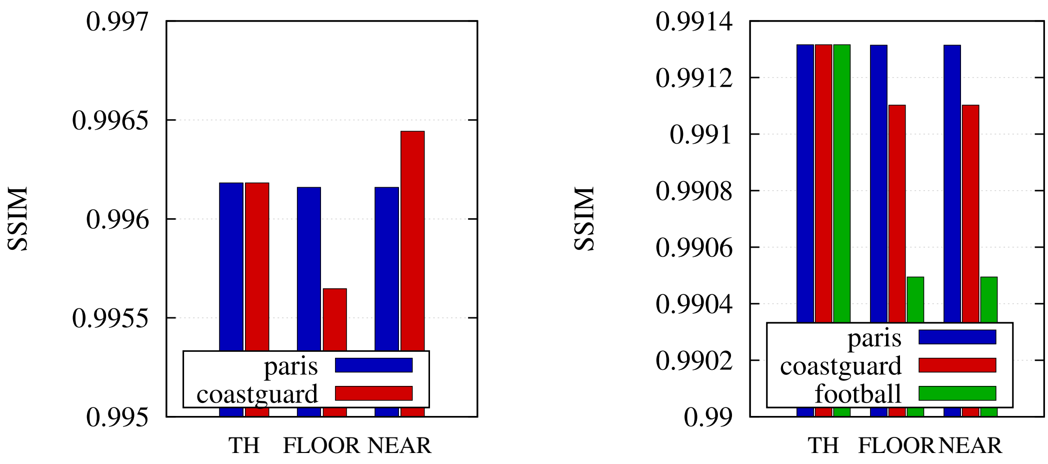


Figure 5.4: Rate assigned to each video flow using RF. TH is the output of the RM algorithm, while FLOOR and NEAR are the assignments using the corresponding strategy. The dashed line represents the bottleneck rate.



(a) 2 flows

(b) 3 flows

Figure 5.5: Resulting SSIM index of video flows using SF. TH is given by the output of the RM algorithm, FLOOR and NEAR refer to the corresponding strategy.

Video	RF		SF	
	FLOOR	NEAR	FLOOR	NEAR
paris	0 (0%)	0 (0%)	0 (0%)	0 (0%)
coastguard	0 (0%)	0 (0%)	0 (0%)	0 (0%)
football	0 (0%)	0.325 (9.03%)	0 (0%)	0.063 (1.75%)

Table 5.2: Freezing time in seconds for each video flow (values in brackets indicate the freezing time as fraction of video length).

The first, called *FLOOR*, consists in choosing the maximum available rate that is smaller than or equal to the given rate r. Formally, if the set of available rates is denoted $\bar{\mathbf{r}} = \{r_1, r_2, \ldots\}$, the chosen rate is

$$r_i = \max\{r_k \in \bar{\mathbf{r}} \mid r_k \leq r\}. \tag{5.1}$$

The second policy, called *NEAR*, simply chooses the available rate that is the closest to the given rate r. Formally, the chosen rate is given by

$$r_i = \underset{r_k \in \bar{\mathbf{r}}}{\operatorname{argmin}}\{|r_k - r|\}. \tag{5.2}$$

To evaluate the impact of the chosen strategy on the proxy performance, an experiment involving three clients has been set up. The first client sends the request for the streaming of video *paris*, which will be immediately activated, then, 20 seconds later, the second client starts playing the *coastguard* video, while video *paris* is still being streamed. Finally, after other 5 seconds, the *football* video starts playing, for a total of three simultaneously active videos. All video flows have been assigned class bronze. Therefore, SF and ISF perform in the same way, so that only results obtained using SF are shown. The rate of the bottleneck is set at $R = 12041$ kbit/s, which corresponds to the rate of the full quality version of *paris* video.

As we can see from Figure 5.3 and Figure 5.5, the NEAR strategy always provides an SSIM value for the video flows closer to the theoretical one with respect to the FLOOR strategy. The downside of this strategy, as can be seen in Figures 5.2 and 5.4, is the possibility to exceed the available channel rate, thus causing the playout buffer to run empty. This causes the phenomena known as freezing, where the video stops playing waiting for the buffer to fill up again. This phenomena can be seen in Table 5.2 where the freezing time for the videos in various cases are reported.

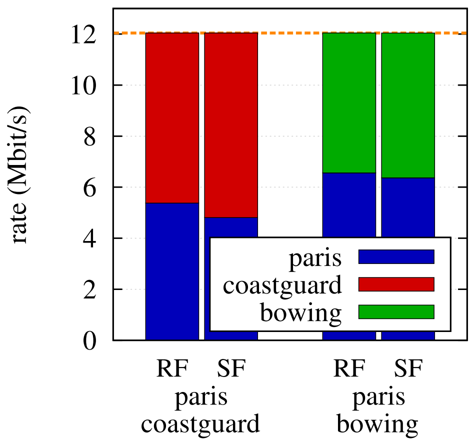
In fact, we can see that RM algorithms allocate in each case all available resources, but the mapping strategy to available video rates either provides always an inefficient channel allocation because of the unused bandwidth, or a significant probability of exceeding available channel rate as in the case of two videos in Figures 5.2 and 5.4.

So, even if the NEAR strategy provides a lower amount of unused channel and SSIM values closer to the theoretical values, the probability to have freezing phenomena is relevant. Given that the whole point of a resource mangement proxy is to avoid any significant freezing event, the best strategy appears to be the FLOOR strategy, which will be used in all the following experiments.

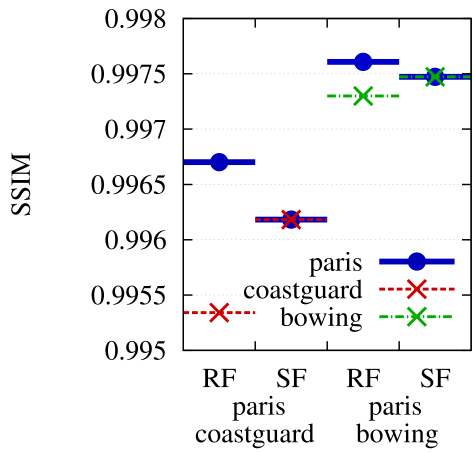
5.2 Comparison between RF and SF

Now the behaviour of RF and SF will be compared when two video flows are active, with a bottleneck rate of 12041 kbit/s and 6021 kbit/s. Results will be derived using two different sets of active videos with different characteristics. The videos used are:

- *coastguard*: it has a very steep RSF-SSIM curve, meaning that a small rate reduction implies a large reduction in its SSIM index;
- *bowing*: its RSF-SSIM relationship is gentle, implying a small SSIM reduction even for a quite large reduction in rate;

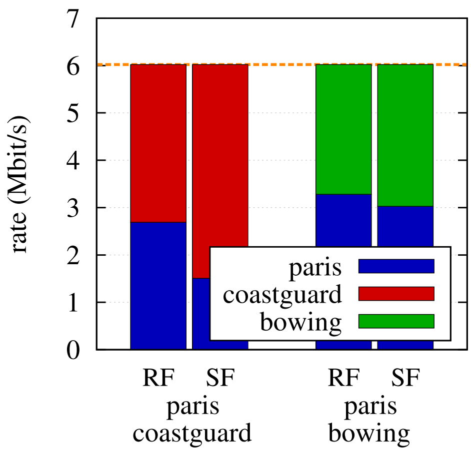


(a) Video rates, the dashed line represents the bottleneck rate

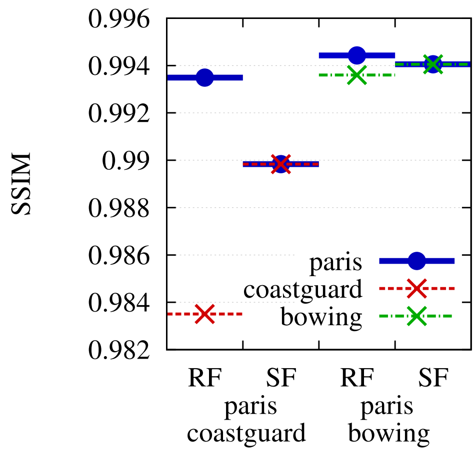


(b) SSIM index

Figure 5.6: Theoretical video rates and SSIM indices as outputted by RM algorithms for two simultaneously active video flows, using videos *paris* and *coastguard* or *paris* and *bowing*, with bottleneck rate 12041 kbit/s.

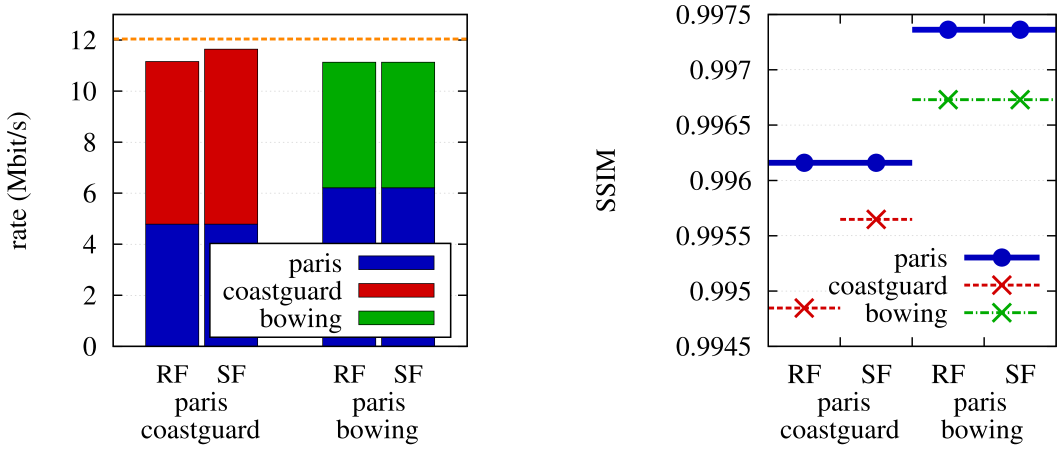


(a) Video rates, the dashed line represents the bottleneck rate



(b) SSIM index

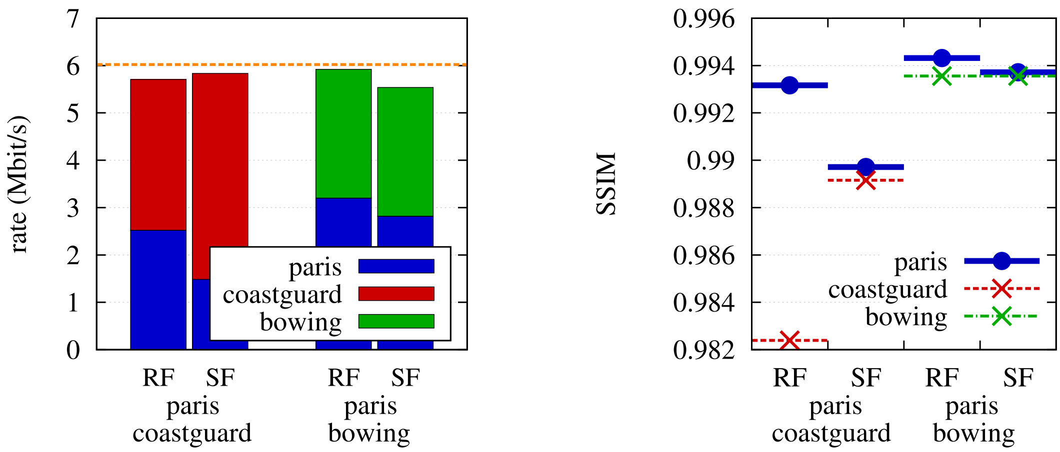
Figure 5.7: Theoretical video rates and SSIM indices as outputted by RM algorithms for two simultaneously active video flows, using videos *paris* and *coastguard* or *paris* and *bowing*, with bottleneck rate 6021 kbit/s.



(a) Video rates, the dashed line represents the bottleneck rate

(b) SSIM index

Figure 5.8: Resulting video rates and SSIM indices for two simultaneously active video flows with discrete quantization levels, using videos *paris* and *coastguard* or *paris* and *bowing*, with bottleneck rate 12041 kbit/s.



(a) Video rates, the dashed line represents the bottleneck rate

(b) SSIM index

Figure 5.9: Resulting video rates and SSIM indices for two simultaneously active video flows with discrete quantization levels, using videos *paris* and *coastguard* or *paris* and *bowing*, with bottleneck rate 6021 kbit/s.

- *paris*: its RSF-SSIM curve behaviour is halfway between those of the other two videos.

As we can see from Figure 5.6a, when the active videos are composed by the couple *paris* and *coastguard*, the *coastguard* flow gets assigned by the RF a higher rate than that assigned to the *paris* video, because the full quality rate of *coastguard* is bigger than the one of *paris* video. Nevertheless, the SSIM value of *coastguard* video is still way lower than the one for *paris* video, as we can see in Figure 5.6b. To get equal SSIM values for both videos, SF allocates even more rate to the *coastguard* video, allowing them to reach an SSIM value of 0.996182, which is slightly larger than the average between the SSIM indices of the two videos for the RF case, equal to 0.996021. Since all videos belong to the same class, ISF and SF provide identical results.

When the active videos are *paris* and *bowing*, instead, RF assigns a lower rate to the *bowing* video than to *paris* video. But, in this way, *paris* video still gets higher SSIM, so that to reach the same SSIM value for both videos, SF allocates to *bowing* video an even higher rate than that allocated by RF, while reducing the rate of *paris* video. With these videos the SF provides an average SSIM equal to 0.997473, which is again slightly larger than the one obtained using RF, where the average SSIM is 0.997453.

It is important to note that using SF, the gap between the rates of *paris* and *coastguard* videos is wider than that given by RF. With videos *paris* and *bowing*, instead, the SF provides a more even rate allocation between the two videos with respect to the allocation calculated by RF. This indicates that, even if the feature used by RF to calculate the optimal allocation (the full quality rate of videos) is correlated to the quality-rate curve, this characteristic does not contain all the information needed to obtain a real fairness on quality, like the one reached by SF.

Results with the bottleneck rate of 6021 kbit/s (Figure 5.7) confirm what already observed in the previous paragraphs, showing that these results do not depend on the bottleneck rate.

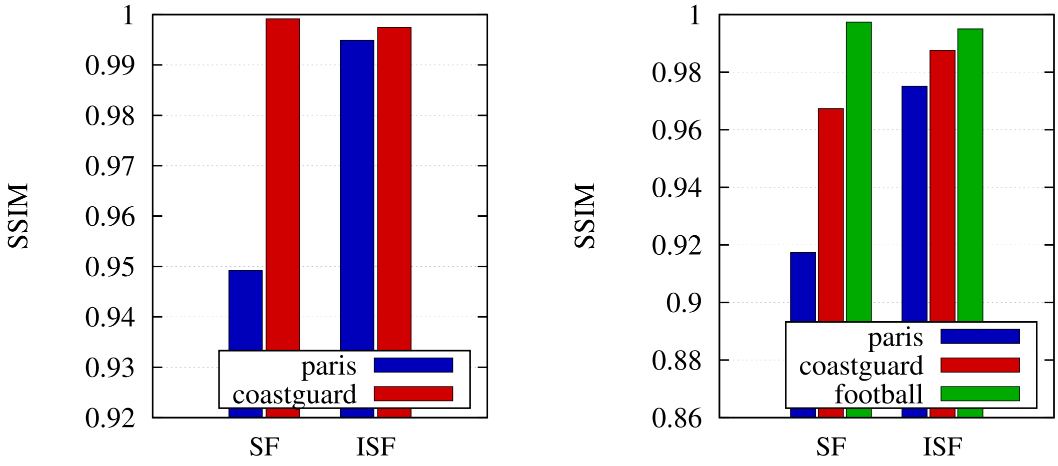
Plots built using the real values of rate and SSIM for streamed video (instead of the theoretical results given by the RM algorithms) show that small differences in rate allocation between the algorithms, as in the case of videos *paris* and *bowing* in Figure 5.6a, often do not make practical difference (Figure 5.8a), because they are evened out by the application of discrete quantization levels. Bigger differences in rate allocation between RF and SF, instead, affect the real flow rates and SSIM values, like in Figure 5.9. Another thing to note analyzing the real SSIM values of video flows (Figures 5.8b and 5.9b) is that, obviously, exact SSIM fairness can not be reached even using SF, but, in this regard, SF is still much more capable of providing quality fairness with respect to RF.

5.3 Comparison between classless and classfull RM algorithms

One of the most important part of RM algorithms is related to the management of quality classes. In fact, this feature is one of the most important selling points of the resource amangement proxy, because clients can not manage quality classes and, even if they could, the class assigned to a user could be overridden by client, which is under the user's control.

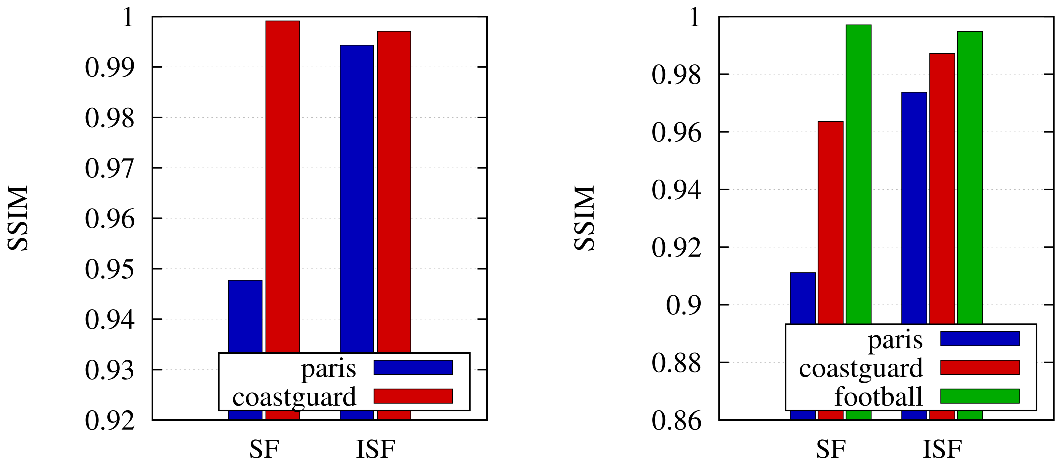
With this experiment, we will compare rate allocation and SSIM values obtained by appointing different classes to flows using both SF and ISF. As already stated, these two algorithms perform equally in the case of single class video flows. Videos used are the usual *paris*, *coastguard* and *football*. Experiments with a single class have been conducted appointing bronze class to all flows. In experiments using multiple classes, instead, video *paris* has been assigned bronze class, video *coastguard* has been assigned silver class and video *football* has been assigned gold class.

As we can see from Figure 5.5, using SF with a single class for all video flows leads to all flows having the same SSIM value, thus reaching a perfect SSIM fair-



(a) 2 flows (b) 3 flows

Figure 5.10: Theoretical SSIM indices determined by RM algorithms for video flows assigned to different QoE classes, using bottleneck rate 12041 kbit/s.



(a) 2 flows (b) 3 flows

Figure 5.11: Resulting SSIM indices for video flows assigned to different QoE classes, using discrete quantization levels and bottleneck rate 12041 kbit/s.

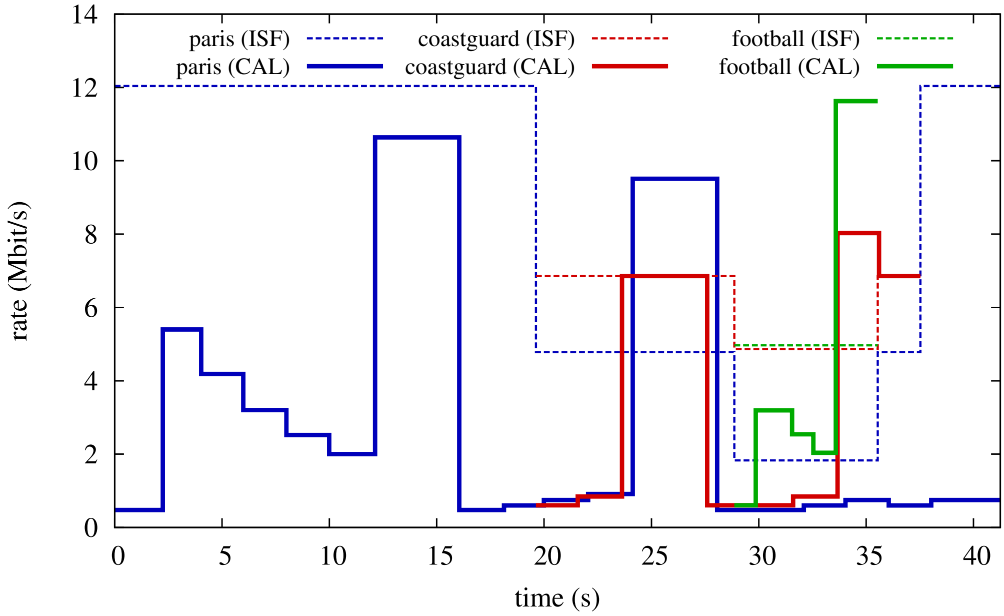
ness, as already stated before. When analyzing results obtained using SF with multiple classes (Figure 5.10), instead, all flows have an SSIM value equal to the sum of the baseline SSIM for each class and an increment α in common between all classes. This result is in accordance with the theoretical explanation of SF in Section 2.2.1. In particular, the increment is $\alpha = 0.049164$ when two videos are active and $\alpha = 0.017349$ when three videos are active. With respect to the classless case, there is now an increase in SSIM value for *coastguard* and *football* videos, to the detriment of *paris* video, which gets a low SSIM value because of its low quality class.

With respect to the SF classfull case, the ISF classfull scenario has an increment in SSIM values for low quality classes, with a compensating decrement for high quality classes. In particular, in the case of two videos, *paris* has an increment of 0.046, while *coastguard* has a decrement of just 0.002 in SSIM value. In case of three active flows, *paris* video has an increment of 0.058 and *coastguard* gains 0.020 in SSIM value, while *football* is affected by a SSIM decrement of just 0.002. This confirms the validity of the reasoning behind ISF: a minimal loss on SSIM for gold flows allows for big quality gains in the other classes. This is because RSF-SSIM graph (Figure 2.1) is almost flat for RSF near 0, so that a rate decrement in that region does not affect significantly the SSIM value.

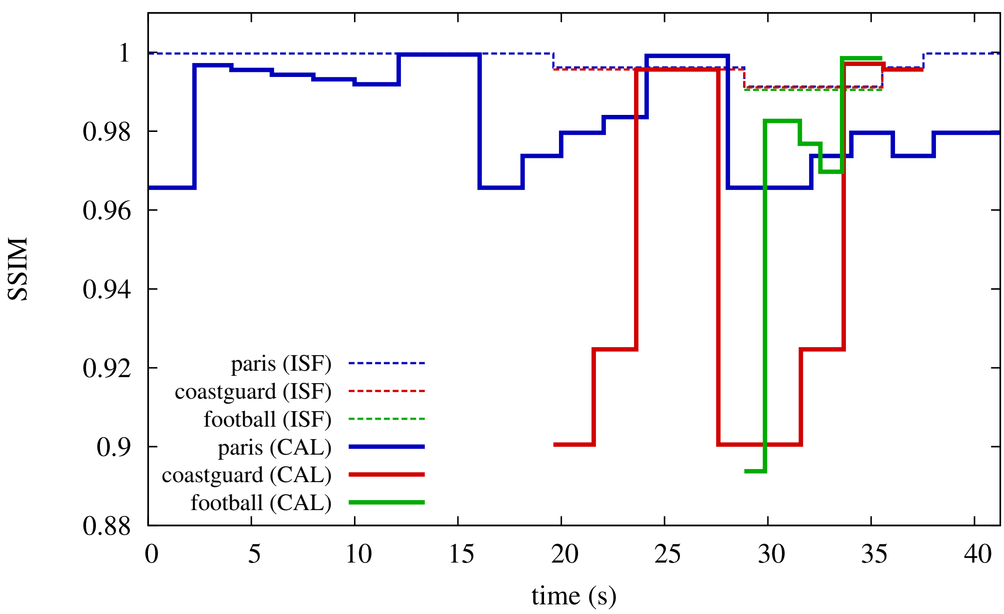
Both theoretical and experimental results from RM algorithms (Figures 5.10 and 5.11) show the same behaviour concerning this aspect, so that the effects of discrete quantization levels are not significant when comparing these algorithms.

5.4 Comparison between RM proxy and client adaptation logic performance

The objective of this experiment is to find out if the use of RM proxy can actually provide better performance than the use of client adaptation logic alone. The experiment consists in the successive activation of videos *paris*, *coastguard* and



(a) Rate values



(b) SSIM values

Figure 5.12: Time evolution of video flows rate and SSIM with ISF and client adaptation logic (CAL).

Video	SF	CAL
paris	0 (0%)	0 (0%)
coastguard	0 (0%)	0 (0%)
football	0 (0%)	2.385 (66.25%)

Table 5.3: Freezing time in seconds for each video flow, values between parenthesis indicate the freezing time as fraction of video length.

football. Results in terms of video rates, SSIM indices and freezing time have been collected using both the adaptation logic integrated in the clients (indicated with CAL in the following) and the use of RM proxy. Given that, without the proxy, clients can not be divided in quality classes, all video flows have been assigned to quality class bronze when using the RM proxy, to get results comparable to the ones obtained with the use of client adaptation logic. The RM algorithm used in the proxy is ISF (it is to note that SF performs as ISF when a single class is used for all video flows).

In Figures 5.12a and 5.12b we can see the rates and SSIM indices for the video flows over time. The first thing to note is the oscillatory behaviour of rate and SSIM values obtained using the client adaptation logic alone. This is because the clients do not know the bottleneck rate, thus they have to start the play-out with the lowest quality version of the video and then try to get progressively better quality segments until the segment download time becomes too high and they have to resort to a lower quality representation. The first problem with this approach is that the client can not provide a high quality vision from the very beginning of the video, as RM proxy allows instead. The second problem appears when another video starts playing: immediately after this event, in fact, clients of the already active flows keep downloading a high rate version of the videos, using more channel resources than what available, thus resulting in freezing events with high probability. In these occasions, the playout buffer role is really important, because it also needs to hide the channel congestion other than the usual jitter problems. When the clients find a congested network, they all resort to an extremely low quality version of the videos at first, trying to progressively increase the flow rate over time. This behaviour causes the spiky rate and SSIM evolution in time, visible in Figure 5.12a. This brings the client adaptation logic to incurr in significant freezing events, summarized in Table 5.3, and yields significantly lower video quality than using the RM proxy. The consequence of this spiky behaviour is the alternate reproduction of medium-high quality segments and low quality segments, which worsens the perceived quality even more. In fact, the continuous variation of the video quality makes much more evident the image degradation than a smooth playout with relatively low but constant quality.

The drawback of using the RM proxy is the need to know the available bandwidth across the network bottleneck. If this bandwidth is not reserved for video flows with other mechanisms, like diffserv, it must be estimated, giving the same problems as those experienced by the client adaptation logic. However, in this case the competing traffic does not include other video flows, which are demanding in terms of bandwidth, but only less bandwidth hungry transmissions, which make the above mentioned problems much less serious.

Chapter 6

Conclusions

In this thesis, different Resource Management algorithms have been described and compared via simulations. Then, these algorithms have been used to build a Resource Management proxy, which allocates channel resources in a QoE-aware manner. The RM algorithms analyzed are: Rate Fairness, which assigns the rate to each video flow in a QoE-agnostic way, SSIM Fairness, which allocates resources such that all video flows get an SSIM value equal to their class threshold incremented by a factor equal for all flows, and Improved SSIM Fairness, which exploits the RSF-SSIM curves behaviour to improve SF performance.

From simulative results, ISF appeared to be the clear winner, enabling the video flows to reach high SSIM values while accepting a high number of requests.

Experimentations with the RM proxy proved that the use of the proxy is able to drastically improve the quality of video flows with respect to the use of client adaptation logic alone, while avoiding freezing phenomena. Again, the use of ISF proved to perform really well both in classless and classfull cases. In particular, with this algorithm, the use of classes proved to be a viable way to provide different QoE to different users, without penalizing too much users belonging to low QoE classes.

Summing up, the use of RM proxy is particularly effective in increasing the user experience regarding video playout, and, with the growing adoption of DASH technology, this technique is also suitable for large scale implementation.

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