The final version of this paper has been accepted for publication in the
Proceedings of the 2015 IEEE International Conference on Communications (ICC), 8-12 June 2015, London - UK
Digital Object Identifier 10.1109/ICC.2015.7249297

# QoE-aware Video Rate Adaptation algorithms in multi-user IEEE 802.11 wireless networks

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***Abstract*—The spreading of video streaming services in the last few years is presenting new challenges in wireless networking; Video Rate Adaptation (VRA) is a technique that optimizes the bandwidth usage by adapting video quality as network conditions change. We propose two Quality of Experience (QoE) aware algorithms that perform VRA while guaranteeing user satisfaction.**

## I. Introduction

In the last few years, video streaming has become the most important source of traffic in the Internet; it represented 60% of total consumer traffic in 2013 [1], and the predicted share for 2018 is higher than 75%.

The extremely fast growth of video streaming, as well as the increase in bitrate caused by the advent of HD videos, can cause resource allocation problems in wireless networks. While the data rates of wired connections have been increasing steadily, wireless and mobile networks face a hard limit given by the available bandwidth, and even advanced schemes such as 802.11n [2] might not be enough to satisfy the demands of users.

Another problem of video streaming optimization is that the relation between the lower layer network parameters such as error rate and delay and the user's final experience is not easily predictable; if a rate increase results in negligible QoE improvement, the transmitted data are ultimately useless. QoE-aware algorithms take this factor into account by considering the effect of resource allocation decisions on objective QoE measures. Structural Similarity Index (SSIM) [3] is one of the most popular objective metrics in the literature, as it has been found to correlate closely to perceived quality.

Two of the most common Quality of Service (QoS) schemes are Call Admission (CA), which has already been used with success for Voice over Internet Protocol (VoIP) traffic [4], and Video Rate Adaptation (VRA); CA algorithms make a decision when a user requests a video and block the request if the network is too congested to support the additional load, while VRA algorithms adjust the bitrate of the video using various compression algorithms, which have an impact on the perceived QoE. VRA and CA are often combined, allowing for greater efficiency by adapting the video quality to changing network conditions after the streaming has started, or blocking it completely in case of excessive congestion.

In this paper, we propose two QoE-aware algorithms that work by dividing the video into short segments, which are stored in a server and whose quality (with respect to the highest-quality version) is known; they then use different schemes to choose the quality of the next chunk for each video, or even block new requests entirely. We also devise a QoE-unaware benchmark algorithm that acts as a baseline to compare the performance of the other algorithms.

We tested the performance of the new algorithms by simulation in an IEEE 802.11g [5] wireless network. The rest of the paper is organized as follows: Section II is a review of the current state of the art in CA and VRA, while the system model and the proposed algorithms are explained in Section III. The implementation details and the results of the simulations are described in Section IV, while the Section V gives our conclusions and discusses some ideas for future extensions of this work.

## II. State of the Art

Several CA and VRA algorithms for video applications have been proposed in the literature in the last few years.

In [6], Xiao and Li propose an admission control algorithm for enhanced distributed channel access using the IEEE 802.11e standard [7], which is mainly used for delay-sensitive applications; Mohammad [8] and Joseph *et al.* [9] also proposed algorithms based only on Quality of Service (QoS) parameters, validating them by theoretical computations or simulations. In all three cases, the presented algorithms are evaluated only in terms of QoS.

A QoE-aware call admission algorithm has been proposed in [10] by Piamrat *et al.*, who used a neural network to approximate a subjective QoE judgment in real time and developed a CA algorithm to maintain a minimum level of quality for all admitted videos. Although the results of the authors' simulations show some improvements over simpler algorithms based on error probability, the simulation scenario they used is extremely restrictive and does not represent a realistic network. Their algorithm is also extremely simple, as it is based on a three-state machine that does not take into account the expected rate of new clients, nor the different characteristics of the requested videos.

Several dynamic VRA algorithms have been proposed in the last few years, but most are not QoE-aware and use only QoS parameters. The algorithm proposed by Van Beek and Demircin in [11] gives significant QoE improvements when simulated in an 802.11 network, but only considers a single user, thus neglecting the issues related to resource sharing by multiple users. Ozcelebi *et al.* focus on fairness in multi-user systems [12], maximizing QoS in pedestrian environments.

Joseph and de Veciana [13] derived and simulated a model for fair cross-layer VRA that takes QoE explicitly into account in the utility function to be optimized. Their work also considers the effect of temporal variations on perceived QoE, but has not yet been tested in a realistic wireless environment.

Luna *et al.* use VRA in wireless systems for a different purpose: their algorithms [14] are focused on the MAC and physical layers, and aim at increasing the energy efficiency of the transmission as much as possible while satisfying the quality constraints. Although this approach is not relevant in heavy traffic conditions, it may be useful for battery powered devices with stringent energy constraints such as those used in large sensor networks.

A different but equally important application of dynamic VRA is error-free video streaming over HTTP: algorithms to adapt the bitrate and reduce buffering have been implemented in most commercial streaming players, and Akshabi *et al.* evaluate the approaches taken by some of the most successful ones in [15].

Finally, machine learning and QoE-aware algorithms have been tested by some of the authors of this paper in [16], [17] and [18]; some of the results of these works are used as a foundation for our model and simulation. The approach of [16] is similar to the one used in this paper, as in both studies VRA is performed exploiting the SSIM values of the requested videos or Groups of Pictures (GOPs), as in both studies. Basically, the VRA algorithms aim at optimizing utility functions guaranteeing that the SSIM perceived by the users does not go below a certain threshold. The authors propose a way to approximate the SSIM metric with a fourth-degree polynomial and use this estimate as a description of the relation between the QoE perceived by the user and a measure of the rate called *Rate Scaling Factor* (RFS). A clustered version is proposed to reduce the computational complexity of the algorithms: videos with similar characteristics are tagged with the same polynomial coefficients. In [17], rather than estimating the SSIM values of each required video, a machine learning approach is proposed and the SSIM of a GOP is estimated from the size of its coded frames. The procedure is carried out in two steps: first an abstract representation of the raw data is provided in order to capture the descriptive features of the video, then the representation is mapped into the corresponding SSIM coefficients. This approach makes it possible to outperform offline video analysis techniques with reasonable computational costs. Finally, [18] generalizes the approach to a scenario with three classes of users, having different QoE requirements. In this paper, we enrich the scenario with a more detailed wireless access technology, whose characteristics are then considered in the definition of the scheduling algorithms and of users class.

## III. System model and proposed algorithms

### A. System model

The scenario considered in this paper involves a client-server architecture in a wireless network. The server is connected by means of a high-capacity Ethernet link to an Access Point (AP) that acts as base station for a Wireless Local Area Network (WLAN), in which a number of wireless hosts are placed randomly with uniform distribution within a circular area. A possible configuration of the network is shown in Figure 1. At this stage of the work we assume each client's position to be fixed, although the algorithms can be adapted to work with mobile clients as well.

The simulation uses a pool of 38 CIF video clips taken from standard reference sets[1] with different durations and scene dynamic characteristics. Each client sends a request for a random video at random exponentially distributed intervals. All videos are available at 18 different compression levels and higher compression levels have lower bitrate and quality as a result of a coarser quantization after the discrete cosine transform in the H264 video encoding [19]. The video encoding and compressing process is explained in detail in [16].

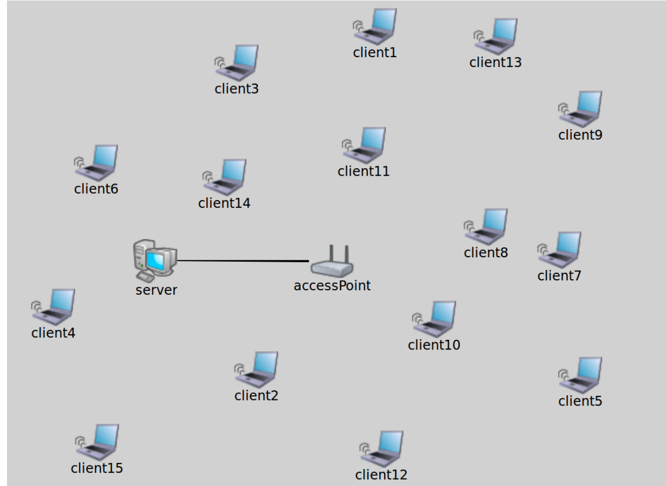


Fig. 1. Network topology

The videos are divided in GOPs of 16 frames each. The client sequentially requests the GOPs, and the VRA block in the Access Point (AP) defines the compression level the server will use to stream the video. Once a video has been admitted, all subsequent GOPs have to be transmitted at the minimum guaranteed quality; the server receives the request, along with the assigned compression level, from the AP and starts the video transmission.

In order to perform VRA, the AP needs to know the duration, bitrate and average quality of each GOP of every video, and the Signal to Noise Ratio (SNR) of the wireless connection of the requesting client.

The choice of SSIM as the metric to evaluate the QoE is due to the fact that it provides a more reliable representation of the perceived quality in comparison to Mean Square Error (MSE) or Peak Signal to Noise Ratio (PSNR). It is calculated over a square window that slides pixel-by-pixel along the whole image. The SSIM between the two corresponding windows $X$ and $Y$ of the original and received frames is computed as follows:

$$SSIM(X,Y) = \frac{(2\,\mu_X\mu_Y + c_1)\,(2\,\sigma_{XY} + c_2)}{(\mu_X^2 + \mu_Y^2 + c_1)\,(\sigma_X^2 + \sigma_Y^2 + c_2)} \quad (1)$$

where $\mu$ and $\sigma$ are the mean and variance of the luminance components of the considered windows, while $c_1$ and $c_2$ are corrective coefficients needed in case of a weak denominator.

### B. Algorithms

We defined two families of algorithms: classless (S) and class-based (C). The classless algorithms have the same quality threshold for all clients, while the class-based versions use three different quality thresholds (gold, silver and bronze), which are based on the SNR, and hence on the distance from the AP; as clients with a low SNR use more transmission resources, their minimum quality level is lower.

[1] http://www2.tkn.tu-berlin.de/research/evalvid/cif.html

The QoE-aware algorithms we propose are centralized, eliminating most of the performance problems of distributed algorithms: as the AP has a complete knowledge of the network conditions and adjusts the compression levels of all clients accordingly, the algorithms completely avoid congestion and exploit the bandwidth in the most efficient way. A potential drawback is that the AP needs to have the computational power to perform a possibly very complex cross-layer optimization; as no additional signaling is required, the centralized algorithms do not contribute to network congestion, but further work may explore content-aware distributed versions of the following algorithms. Our algorithms estimate the fraction of the AP transmitting time needed for streaming the video; once the physical modulation is derived from the SNR, the algorithm calculates the application layer capacity $C_i$ for each client $i$. If there are $n$ active clients in the network, and each client has a video bitrate $R_i$, the network stability constraint is given by

$$\sum_{i=1}^{n} \frac{R_i}{C_i} \leq 1 - s \tag{2}$$

where $s$ is a safety margin against rate fluctuations. Although the algorithms are designed to maintain a minimum SSIM level, the perceived quality of a single video might temporarily dip slightly below the threshold, as the SSIM associated with a given compression level can fluctuate during a video. After finding the optimal compression level configuration for all clients according to the algorithm used, the AP performs CA and admits or blocks the new request based on this configuration.

*BM-S:* The first algorithm we implemented is the *Benchmark-Single* (BM-S) algorithm, whose behavior mimics that of state-of-the-art VRA algorithms, which are entirely client-side, with all the issues of distributed algorithms. Clients that implement BM-S autonomously choose the required compression level according to the network conditions. The congestion level is estimated by each client based on the time between the reception of the first and the $M$-th frame of a GOP. If such time is above a given threshold, the client increases the compression level as it deems the current rate to be too high, leading to a decrease in the video QoE. On the other hand, if the arrival time of the $M$-th frame stays below the threshold for 3 consecutive GOPs, the client judges the connection to be good and hence tries to increase its video quality by lowering the compression level. The inter-arrival time is a simple client-side measure of the occupation of the AP transmission queue; if the network is congested, the packets will arrive later due to queueing delay, and the client can sense this without any additional overhead.

The BM-S algorithm is not content-aware: it only has a maximum compression level, which is the same for all videos and represents the minimum acceptable video quality. If a client's quality drops below the minimum, the video stream is dropped, as the network is too congested to continue. The maximum compression level is also the starting level for all clients when they request a new video.

*QB-S:* The *QualityBased-Single* (QB-S) algorithm aims at providing the highest video quality to as many users as possible, increasing the video compression level as much as possible without violating the minimum SSIM constraint. It basically tries to find the best configuration that admits the new client while respecting all the others' quality demands (otherwise the new user is simply not admitted). Whenever a new stream is requested, QB-S initially tries to stream all admitted videos at compression level 1, i.e. at the highest quality. If this configuration's total rate exceeds the available bandwidth, violating the stability condition (2), the algorithm finds the video with the biggest SSIM margin from the threshold and raises its compression level by 1. This operation is repeated until an acceptable configuration is found; if the SSIM of any of the already admitted videos drops below the threshold, QB restores the previous compression levels and blocks the new request, otherwise it admits the request and starts using the new configuration.

*TB-S:* The *TimeBased-Single* (TB-S) algorithm also tries to stream all videos at the highest quality, but unlike QB-S it tries to divide the transmission time between the clients as fairly as possible: if $n$ users are streaming and a new client requests a video, the algorithm checks whether all video streams can meet their own quality threshold using $\frac{1}{n+1}$ of the available time (instead of $\frac{1}{n}$). Moreover, if a client uses less than its share to transmit the video at the highest possible quality, its remaining time is shared among the other clients to exploit the bandwidth more efficiently, mimicking the Generalized Processor Sharing (GPS) service policy. The new request is admitted only if the algorithm finds a configuration that respects the quality constraints without any of the clients exceeding its transmission time share.

We also propose class-based versions of QB-S and TB-S, namely *QualityBased-Classes* (QB-C) and *TimeBased-Classes* (TB-C). As explained above, the class-based algorithms have the same structure as the classless ones, but consider three different quality thresholds (gold, silver and bronze).

Finally, we define the *Benchmark-Classes* (BM-C) algorithm in which the clients choose their maximum compression level based on their SNR. This algorithm provides a meaningful baseline for QB-C and TB-C, as it operates with the same quality thresholds.

### C. *Performance metrics*

We will evaluate three metrics in the simulations: firstly, the video blocking probability for each quality class, secondly, the average quality of the admitted videos, and finally the probability that a client's SSIM will go below the minimum threshold for its class. We expect TB-S and TB-C to have slightly higher blocking probabilities, especially for clients that are more distant from the AP, while QB-S will tend to flatten all videos to the threshold quality level to admit more users, also being more fair in terms of QoE among the admitted users.

## IV. Simulation and Results

### A. *Simulation scenario*

The simulation scenario was implemented in the network simulator Omnet++ [20]; the Inet package was used for most of the elements of the network.

The link between the server and the AP is a 100 Gbps Ethernet, while the wireless network is based on the IEEE 802.11g standard, which uses an OFDM modulation scheme and operates in a 20 MHz band centered at 2.4 GHz. It provides a maximum physical layer bitrate of 54 Mbps, but the available application layer rate is limited by the overhead, with a maximum nominal value of 31.4 Mbps. The actual application layer bitrate might be even lower, as the Auto Rate Fallback (ARF) algorithm uses less efficient modulation schemes for lower SNR values. The maximum transmit power for the network is set to 20 dBm and the thermal noise level of the channel is -100 dBm.

In the simulations, we uniformly distributed 15 clients in a circle of radius 150 m. The thresholds for the quality classes are 20 dB and 12.35 dB: clients with an SNR above 20 dB have a minimum SSIM of 0.99, while clients with an SNR between 12.35 dB and 20 dB have a minimum SSIM of 0.98. All clients with an SNR lower than 12.35 dB belong to the bronze class, but are admitted only if they can meet a minimum required SSIM of 0.96; hence, all admitted clients are guaranteed to have a good video quality. In the classless algorithms, all clients are placed in the gold class. The SNR thresholds for gold and silver class are set to guarantee an application layer rate of about 20 Mbps and 10 Mbps, respectively; the bronze class has no minimum SNR requirements, so its rate may go as low as 1 Mbps, but is actually constrained by the maximum distance of a client from the AP. The maximum compression levels for the BM-C algorithms are 9, 11 and 14 for the three classes (BM-S uses 9 for all clients); these values were calculated by averaging the highest compression level above the quality threshold for the three classes over all videos and GOPs, and as such are only approximations of the quality threshold. We expect BM-S and BM-C to have a higher quality fluctuation than the other algorithms because of this approximation.

The BM-S and BM-C algorithms measure the elapsed time after $M = 10$ frames; as the inter-frame time is $T = 33$ ms, the threshold time after which the client tries to compensate for congestion is $M \cdot T + g = 0.36$ s (where $g$ is a safety margin set to $0.1 \cdot M \cdot T$). The safety margin $s$ that ensures network stability when using the other algorithms is equal to 0.05.

The video streams are represented by Variable Bit Rate UDP flows, and the server uses the actual video traces to determine the size of the packets to send to the clients. The parameter of the exponential distribution of the time between requests is set in order to have an average offered application layer traffic of 80 Mbps and 160 Mbps (with all active clients receiving video at the best quality), so that the wireless link is saturated and some blocking needs to take place.

The scenario ran for 5000 s and was repeated with 10 different random placements of the clients; the same spatial and time configurations were used for all the algorithms and for both levels of traffic to ensure a fair comparison.

### *B. Results and analysis*

The first metric we consider is the video blocking probability of the algorithms, which is actually a dropping probability for BM-S and BM-C, that perform no initial CA.

Figures 2 and 3 clearly show that the QB-S and TB-S algorithms collapse in high traffic conditions; QB-S's blocking probabilities rise as high as 80% for the bronze class, and TB-S also suffers when compared to QB-C and TB-C. The efficiency of QB-C and TB-C is clear in the figures: the blocking probabilities are almost uniform among the three classes, whereas QB-S and TB-S clearly privilege clients with high SNR.

Moreover, the overall blocking probability is lower for class-based algorithms, and particularly for QB-C, because

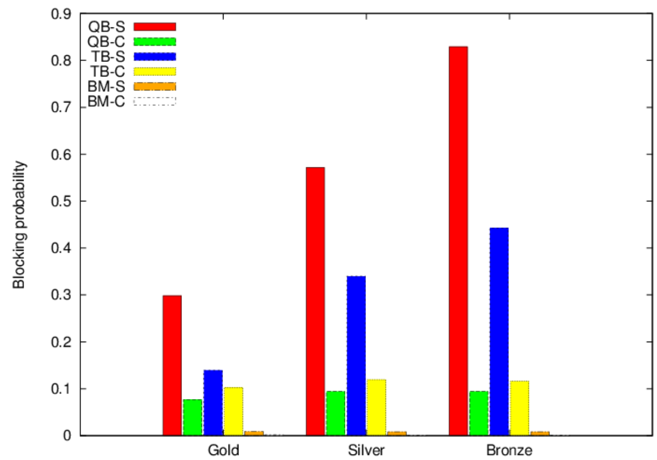


Fig. 2. Blocking probability for the three classes of clients with 160 Mbps offered traffic

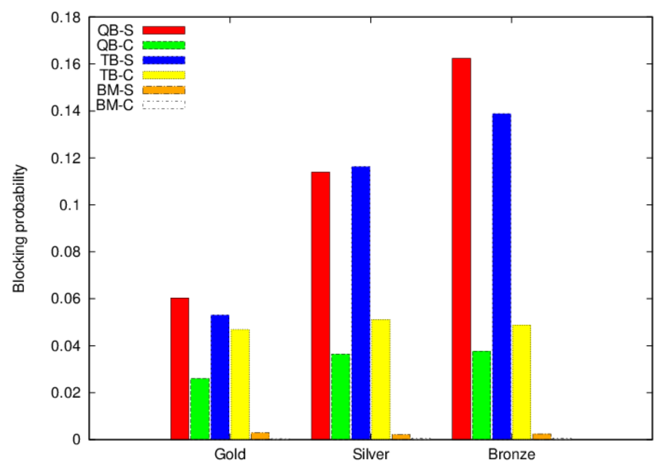


Fig. 3. Blocking probability for the three classes of clients with 80 Mbps offered traffic (please note the different scale)

admitting a client with low SNR when the traffic is low may block subsequent requests. In the class-based algorithms, the AP can raise the distant client's compression level to mitigate this effect. Nonetheless, the quality threshold we set in the classless version of the algorithms is very high (SSIM of 0.99) and this choice increases the blocking probability. It is interesting to note that QB-C outperforms TB-C, while QB-S outperforms TB-S. QB-S and The nature of QB-C benefits from the class structure as they consider channel quality only marginally when determining the best compression level configuration, while TB-S and TB-C work by dividing the transmission time fairly, already taking SNR into account.

BM-S and BM-C exhibit extremely low blocking probabilities, with values below 1% even in the high traffic scenario. In fact, as the other metrics show, BM-S and BM-C work very close or even below the imposed quality thresholds and can admit almost all requests but with poorer QoE.

TB-S shows an advantage in the average SSIM for the admitted videos over QB-S and BM-S, as Figure 4 shows. BM-S yields the worst quality levels among the classless algorithms, confirming the previous analysis: it only drops a few clients to the detriment of the QoE of all users.

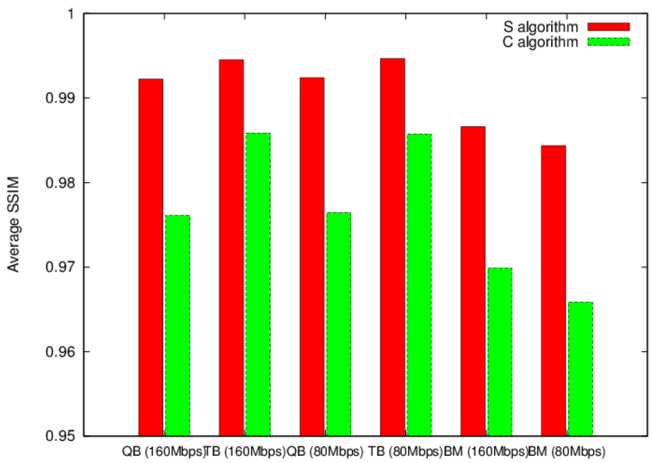


Fig. 4. Average SSIM for each algorithm

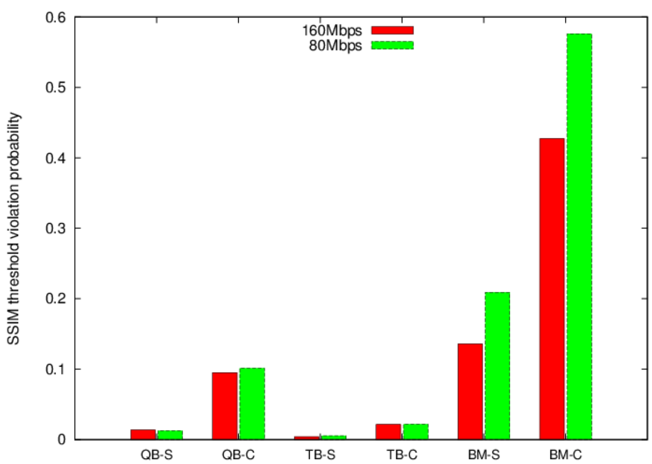


Fig. 5. Probability of SSIM threshold violation for each algorithm

Traffic seems to have almost no effect on average quality, as the scenarios with 10 MBps and 20 MBps offered traffic present essentially the same SSIM values for QB-S, QB-C, TB-S and TB-C; as the channel is already saturated with the lower traffic, this was to be expected. QB-C and TB-C obviously pay the lower blocking probabilities with a lower average quality caused by decreasing the silver and bronze class thresholds, but the difference between the algorithms is the same; BM-C achieves a very low video quality, even below 0.97.

Figure 5 shows that the clear advantage of QoE-aware algorithms is in the last metric: the probability of going below the quality threshold. As BM-S and BM-C only consider average SSIM values and do not take into account the specific dynamics of each video, it is inevitable to have some SSIM fluctuation, which results in the QoE dipping below the minimum threshold. BM-S and BM-C yield quality levels below the threshold more often as traffic increases, because of their lax dropping policy.

Even the QoE-aware algorithms may go below threshold, but with lower probability; this is inevitable, as the algorithms recompute the compression levels at each new video request instead of every GOP, which would put a heavy computational strain on the Access Point.

In general, TB-S and TB-C perform better than QB-S and QB-C, as they work with a larger SSIM margin from the quality threshold, and this is particularly evident for QB-C and TB-C. The C algorithms have a higher probability of going below threshold because of video quality fluctuation: they operate at higher compression levels for the bronze and silver classes, and the quality variation between successive GOPs increases with the compression level. A mathematical explanation can be derived from the polynomial expressions in [17]: as almost all polynomials have a negative second derivative when the SSIM is between 0.95 and 1, a small fluctuation in the video characteristics can result in a higher quality change when the first derivative is higher, i.e., with lower qualities.

## V. Conclusions and Future Work

In this paper, we developed four different algorithms for dynamic rate adaptation in 802.11 networks. The algorithms are centralized and content-aware, using the actual QoE of the users as an optimization metric. Our simulations proved that they perform well in terms of blocking probability and average user QoE, while keeping all users' qualities above a given threshold.

The centralized QoE-aware algorithms clearly outperform the QoE-unaware distributed BM-S and BM-C, admitting fewer clients but with very high perceived SSIM values. On the contrary, BM-S and BM-C can even yield average SSIM values below the imposed threshold (see Figure 4). Centralized VRA algorithms running at the AP can better exploit the available bandwidth, preventing congestion rather than reacting to it. TB-S outperforms QB-S in terms of both quality and blocking probability, since it considers the transmission time that a new admitted client would occupy, while QB-S only works with SSIM, without considering the cost of changing the SSIM for any given client.

We may handle the VRA problem as an instance of the knapsack problem [21], in which each video GOP has a weight (the transmission time it needs) and a profit (the resulting SSIM). Note that, the knapsack problem is NP-complete [22], so that a polynomial time solution is unknown, though dynamic programming can provide a pseudo-polynomial resolution time. Concerning our algorithms, the TB-S algorithm is closer to the optimum solution of the NP-complete problem, maximizing the overall SSIM, while QB-S is more fair; QB-C and TB-C are more fair to distant users, but the SSIM constraints on the clients are laxer, allowing for a larger solution space.

It would be interesting to evaluate the performance of the algorithms with different quality thresholds, mainly to figure out the real effect of the class-based approach with respect to the classless approach.

Another important parameter to consider is the computational time of the algorithms: TB-S and TB-C are considerably slower than QB-S and QB-C, and this may play an important role in highly dense networks with many users or when the computational capabilities of the AP are low due to energy or hardware constraints.

An interesting item for future work may concern the use of real measurements of the channel occupancy. The improvement in the algorithms' performance strongly depends on the accuracy of the SNR estimate we used: a conservative estimate means that potentially admittable clients may be blocked, so the SSIM would be higher and the blocking probability lower; instead an aggressive estimate may inflate the real QoE and cause unwanted packet losses.

We plan to implement a distributed version of the proposed algorithms to provide better scalability in dense networks and reduce the control action required for the AP.

Another interesting scenario considers mobility: if the clients move and are handed off between different APs, possible improvements of the algorithms include their integration in cognitive networks and the use of mobility prediction models when making video admission decisions.

## Acknowledgment

This work was supported by the project A Novel Approach to Wireless Networking based on Cognitive Science and Distributed Intelligence, funded by Fondazione CaRiPaRo under the framework Progetto di Eccellenza 2012.

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