

Chapter 1

Introduction

Abstract The visual senses dominate the sensory input, accounting for 80 % of perceptual information. This makes video an attractive medium for high density information services. As video enabled services become more present in our lives, our expectations about their performance and reliability is being set. In order to meet customer's expectations, service providers need to be able to deliver increasingly more demanding services with higher quality standards. This development delivers a high toll on maintenance costs and requires frequent upgrades of available resources. Moreover, the upgrade of some wired and wireless transmission technologies is becoming more challenging as technologies are reaching some physical limits. In this situation the need for smarter management strategies is evident as traditional management approaches such as over-provisioning offer little to improve the utilization of the resources. Efficient management of networked services requires understanding of the relationship between different available resources, i.e. computational, storage, network throughput and the delivered quality. However, video-enabled services are operating on a vast diversity of terminal devices, encoding and transmission systems. Motivated by these challenges, this thesis proposes an approach for efficient management of multimedia services. It presents a QoE aware framework for network management that incorporates computational intelligence methods to deal with the evolving complexities in the multimedia systems, and introduces a novel psychometric method that deals with the difficulties of subjective measurements.

1.1 QoE Management Framework

This work proposes an approach for end-to-end management of quality of multimedia services as a framework on top of multitude of underlying technologies [1–4]. At one end is the service provider with the content ready to be served and on the other is the user with its unique characteristics and expectations regarding the content [5, 6]. The framework is designed as a control loop over a general-purpose multimedia system with the goal of matching the properties of the content to the expectations of the consumer, while accounting for the available resources and characteristics of the encoding and the transport systems.

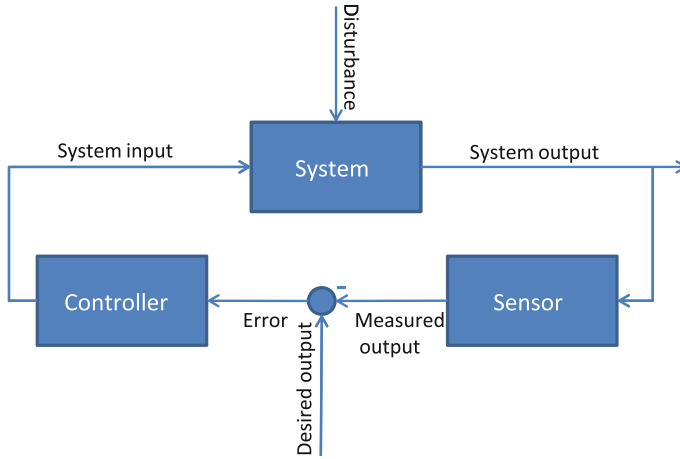


Fig. 1.1 A feedback loop in a control system

As illustrated in Fig. 1.1, a negative feedback control loop consists of three units: the controller, the sensor and the system under control. The sensor measures the system output and compares it with the desired one. The difference is fed into the controller that inputs a control strategy to the system in order to minimize the measured difference. Similarly, the multimedia system controller issues different management strategies based on the measured performance of the system (Fig. 1.2). The

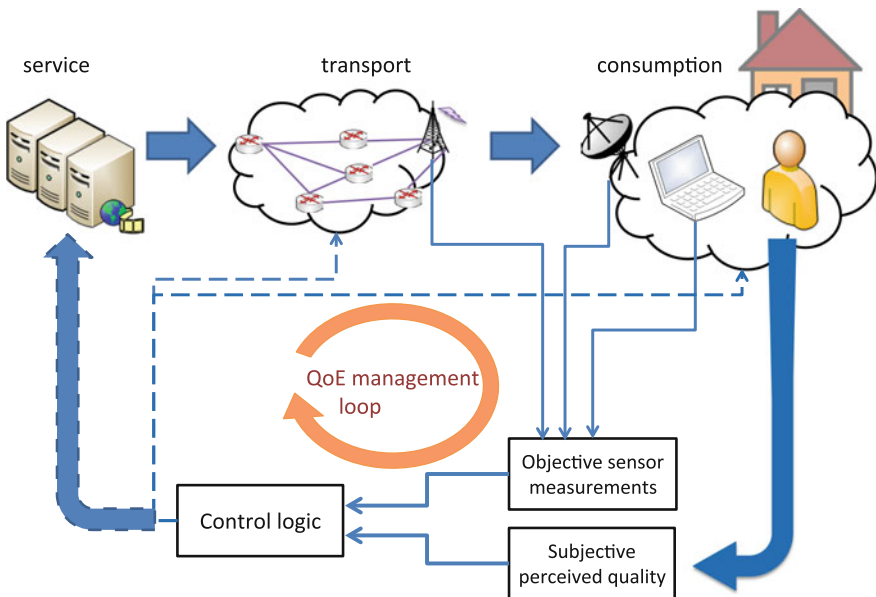


Fig. 1.2 Control loop in a multimedia system

measured value is the subjective QoE perceived by the user and the objectively measured performance by the system components [7]. This value is compared with the desired level of performance and the difference is sent to the controller. The controller can then manage the different system components, allocate necessary resources, execute admission control, or implement other control strategies to achieve the desired level of performance.

This approach offers a viable way to incorporate the large number of factors that affect the quality into the decision process of the controller. It provides for a way to continuously learn and improve the management process based on measurements of the performance and subjective user feedback [8]. In this manner the system maintains a high level of performance with minimum cost in the changing environment. This results in a better utilization of the available resources and a user-centric based management [9–14].

1.2 QoE Definition

In the framework presented here, the system output (or the main performance metric) is the subjectively perceived quality. But how do we understand the term 'quality' in regards to multimedia services?

According to the dictionary, the meaning of quality is: 'The degree of excellence' [15] (of a product, service or activity). Quality as a phenomenon has been examined in many disciplines such as philosophy, business and engineering. More specifically quality involves perception, but also expectations. Some definitions refer to it as a subjective phenomenon: "The feeling of high quality occurs when perception exceeds expectation; the feeling of low quality occurs when perception does not meet expectation [16]." Other definitions focus on more objective, measurable factors: "Degree to which a set of inherent characteristics fulfils requirements." where requirement is defined as need or expectation [17]. In any case, quality is connected with either objective or subjective expectations. More precisely quality is evaluated in regards to the objectively measured or subjective perceived performance.

For services such as telephony, computer networks, and including voice services built on top of them a commonly used metric for quality is the Quality of Service (QoS). QoS defines a set of requirements that need to be met in order for the service to be considered of high quality. These requirements are objectively measurable values and consider performance factors, such as latency and errors in the network. The possibility to set these well defined QoS requirements is enabled by the good understanding of the compression and transmission factors and the subjective perception of speech. However, with the introduction of new types services and varied content, all delivered on a plethora of different devices, understanding 'subjective' perception becomes challenging.

The need to better communicate the service quality has created a need for a precise quality metric. However, instead of continuously expanding and adapting the QoS requirements, the choice was made to introduced a new metric: the Quality

of Experience (QoE) [18]. This metric is better suited for the task, because it is a subjective metric, which captures the effect of all the factors that contribute to the subjective experience.

QoE appears in the literature by different definitions, but generally it is agreed that “QoE measures the quality experienced while using a service” [19]. However, other definitions, such as the one from the ITU-T Focus Group on IPTV (FG IPTV) [20] avoid using the term quality. The FG IPTV defines QoE as the overall acceptability of an application or service, as perceived subjectively by the end-user. The definition of the European Network on QoE in multimedia systems and services is ‘*QoE is the degree of delight or annoyance of the user of an application or service. It results from the fulfilment of his or her expectations with respect to the utility and/or enjoyment of the application or service in the light of the user’s personality and current state*’ [18]. The relation to the subjective perception of the user and its expectations is clearly evident as the defining characteristic of the metric.

Defining QoE is the initial step. In order to successfully build an efficient management system we need to first understand which factors affect it and how [21, 22]. Next we need to understand the relationship between the available resources in the system and those factors [3, 4, 11]. Finally we need to know how to develop control strategies that utilize the available resources in such a manner as to maximize the delivered QoE [23, 24].

1.3 Factors that Affect QoE

QoE is a metric that captures the degree to which our expectations about the service have been met. But, how do we form expectations of a video service and which are the factors that affect it?

We perceive multimedia stimuli first with our senses, and ultimately through the cognitive processes [25] in the brain. Naturally, the characteristics of the human visual and auditory systems are intrinsically linked to the expectations from multimedia services. The auditory system can detect sound in a specific range of frequencies. The typical hearing range for a human is between 20 Hz and 20 KHz [26]. Therefore, reproduction of sound outside of this range will add no additional quality or value to the service; it will only spend more resources. The visual system has elevated sensitivity to contrast in the range of 0.5–16 cycles per degree of visual angle and drops off abruptly on higher frequency [27]. This means that a 1080p HDTV reproduction viewed at a distance between 3 and 4 screen heights can generate patterns on our retina with up to 28 and 37 cycles per degree respectively. This is significantly above the threshold limit for most viewers [28], so increasing the resolution more at this distance will be of little utility.

These examples demonstrate that even though we intuitively consider fidelity of the video and audio as the most significant factor in quality, this has to be taken into the context of the characteristics of the Human Visual System (HVS). Improving certain aspects of fidelity could be without any benefit. On the other hand, limited loss

of fidelity can be just as imperceptible as a flawless reproduction, while delivering significant benefits in terms of resource utilization.

The Human visual and auditory system is not only characterized by a hearing range and a contrast sensitivity range. It is actually very complex and not fully understood. As more characteristics are being discovered the more we can use this knowledge to optimize multimedia services. Some of these limitations are commonly used to improve coding efficiency. For example high spatial frequencies are perceived achromatic [29]. So the amount of data that conveys the colour of the image can be safely reduced in respect to the amount of data that carries the luminance of the image. Other characteristics, such as the masking effects can be used to cover noise in images. If the noise is superimposed over a region of patterns with high contrast, it is significantly less perceptible than over a uniformly coloured region.

Video compression techniques benefit from the varying sensitivity to different ranges of spatial frequency. The video is first transformed into the frequency domain using a discrete cosine transform (DCT) [30]. Then different parts of the image can be encoded with different precision. The last step is known as quantization, whereby high-frequency coefficients are more coarsely quantized than low-frequency coefficients. This is referred to as a lossy compression method. Even though lossy compression can deliver significant benefits in reducing the size of the video, it also causes loss in quality. Quantization causes artefacts such as blockiness, particularly in heavily compressed video, which degrade the QoE.

Further artefacts appear in a video due to modern compression techniques, such as blur, colour bleeding, ringing, false edges and jagged motion [28]. Some of them are present due to spatial compression techniques, which compress individual images. Others are present due to temporal compression method, which reduces the redundancy over multiple images.

Another factor that introduces artefacts is transmission errors [31, 32]. When a packet of video data is lost, has errors or does not arrive on time the video decoder can freeze the video playback or compensate by using some concealment method. Usually this means interpolating neighbouring pixels in space and in time [33]. However, this often results in very noticeable artefacts [34, 35].

When transmission protocols are used to guarantee delivery via retransmission, the lack of network resources leads to delays and freezes in playback. This is a very important factor in the overall experience of the service and can have the most significant impact [36]. It is also established that impairments such as freezes and errors have higher impact on the QoE as their amplitude and frequency increase [37].

Adaptive video streaming technologies allow for reducing the fidelity of the signal in order to avoid freezes. This technique attempts to improve the delivered QoE in cases of restricted resources by downloading the video at lower bit-rates. In this case predicting the right bit-rate level is important as the changes of bit-rate levels during playback have shown to be an impairment on its own. The size of the impairment is proportional to the frequency and amplitude of the change [38].

Naturally, the audio quality is a key factor in the QoE of multimedia services. In fact, audio quality is even more important factor than video quality [28]. Audio compression also benefits from the characteristics of the auditory system. Lossy

audio compression methods cause audio artefacts in a similar fashion to the video compression methods. However, audio compression and encoding requires significantly less resources than video and, because of its importance, its resources are rarely restricted. This often shifts the management focus on the video aspect.

Nevertheless, other more general aspects are also important factors. One such example is the audio and video synchronization. The investigation of media synchronization in [39] concludes that the effect of unsynchronized audio on the QoE depends on the type of content. For some types of content as head and shoulders news broadcast, it has a massive effect. However, for other content the viewers can demonstrate more tolerance. In another investigation of audio and video correlation and lip synchronization Mued et al. conclude that the effects on the perceived quality from audio-video misalignment are different when the content is of a passive or an active communication [40].

Depending on the type of service, there could be other types of impairments such as start-up delays or loss in responsiveness. Overall the factors that affect the QoE are noticeable and are not expected by the viewer. We use our eyes and ears to collect the information from the outside world, but it is the brain that forms our perceptions [41]. The cognition process in the human brain is not understood well, however we know that we do not need all the details to recognize a pattern. Our sensors are designed in this manner, working in restricted ranges. The rest of the details are conceptualized by the cognition process. Nevertheless, with fewer details, the brain needs to work harder to compensate. Sometimes we are willing to do that, because we are watching an old family movie on an outdated technology. But, other times, when we are watching a video on our new and costly mobile device our expectations are high, so the delivered QoE needs to reflect that. As this might be an insurmountable task, measuring QoE in relative terms can be a better solution than attempting to make an inaccurate absolute metric. Pursuing this approach we have developed a method for measuring subjective video quality, which estimates the utility of the system resources in terms of the delivered QoE [42, 43].

1.4 Resources Versus Quality

We have seen that a significant amount of factors contribute to the QoE. However, there is also a clear relationship between these factors and the available resources. Most types of artefacts can be efficiently masked if we can encode the video with enough bits, which also need to be transported by the network accurately and on time. Unfortunately, in any real engineered system the available resources are limited. We can only serve a limited number of users, the network can only transport a limited number of bits per second, and finally storage space and computational power are equally limited. So in order to efficiently manage the system we need to understand the relationship between the allocated resources and the resulting QoE.

The audio and video fidelity have a clear relationship with the available resources. The more bits are used in the encoding process the more accurate the decoded audio and video will be. Uncompressed video contains no encoding degradation, but it requires very large storage space and is not suitable for transmission over a restricted network channel [44]. Compression can be ‘lossless’ where the signal can be exactly reproduced or ‘lossy’ that introduces loss in the fidelity of the signal. Since high definition multimedia content requires significant compression rates (50:1 [45]), lossy encoding techniques present an attractive choice. This is further supported by the leniency of the human visual and auditory system to certain type of distortions. So, the optimal quality is usually achieved in a balanced combination of the parameter values that results in minimal use of resources and a satisfactory level of accuracy.

Each digital video encoding process produces video streams with specific bit-rates. The bit-rate is directly linked to the quality of the video stream and most encoders accept a bit-rate setting as input. It can be either set as a soft (indication) or as a hard (constraint) limit on the encoder in constant bit-rate encoding. In variable bit-rate encoding (VBR), the indicator is usually a quality setting. Therefore, the stream is with constant quality rather than having a constant bit-rate. Based on this setting and the complexity of the video, the encoder compresses the video with a certain average bit-rate. Therefore the bit-rate required to encode the video depends on the type of encoding algorithm, the complexity of the video and the desired quality. Since transport throughput is also a limited resource, the video bit-rate needs to be adjusted accordingly in order to meet the transport network constraints. This is commonly achieved by compressing the video with constant bit-rate encoding (CBR). Typically, MPEG-like algorithms will introduce increasingly larger amounts of artifacts (such as blockiness and blurriness) as the bit-rate is reduced [28]. In other words the video data will be more coarsely quantized in the frequency domain, which will lead to blockiness in the decoded video. The encoder attempts to limit the blockiness effect on low spatial frequencies of the video, which are less perceptible to the viewers. However, very constrained compressions result in highly visible artefacts. Another type of artifact due to encoding is blurriness. This one arises from inadequate temporal fidelity of the encoded video [46].

The loss of fidelity can originate from the pre-encoding process as well. The spatial resolution of the digital video is one of the key factors for the size of the video after encoding. The recording equipment usually has much higher resolution than what can be practically used in video streaming applications. Particularly for mobile devices the resolution needs to be adjusted to the limitations of the devices in screen resolution, computational power or network throughput. It is common to downscale the resolution of the original video before encoding, because it reduces the encoding computation time as well as the size of the resulting video. In cases where the target screen resolution is lower than the input video this pre-encoding process is only beneficial. On the other hand, restricting only the bit-rate can degrade the video more, add more computational on the encoder and on the decoder for downscaling.

In addition to the spatial resolution decrease, there is temporal resolution decrease, or decrease in frame-rate. Frame-rate is usually kept to less than 30 frames per second due to the characteristics of the human visual systems. However frame-rate

acceptability depends on the type of content [6, 47, 48]. Certain types of content that have low mobility and small spatial resolution, frame-rates as low as 10 frames per second can be acceptable. This is particularly useful for very low bit-rate channels in mobile environments where lower frame-rates help achieve the required low throughput. Similar pre-encoding can be implemented in the audio, when sampling rate and sampling frequency are downscaled.

Making the right decisions during the encoding process is key to minimizing the amount of delivered artifacts. Rate distortion theory provides a the theoretical foundation for this problem. The theory is a branch of information theory and deals with lossy data-compression [49]. Based on this theory many rate distortion optimization (RDO) methods have been developed and are commonly incorporated in the decision process of multimedia encoders [50].

Another reason for occurrence of artefacts is errors incurred during transmission. The amount of degradation in quality due to such errors is not easy to estimate due to the very nature of video compression [51]. The removal of temporal redundancy in the video leads to propagation of the errors in multiple frames. This can be constrained by adding more I-frames or reference frames that do not require frame from other data to be compressed. However, increasing the frequency of the I-frames decreases the efficiency of the compression. Another approach to protect the data stream is to use forward error correction techniques [52]. These techniques add redundant data to the stream, which allows recovery of a limited number of bits in case of errors or loss during transmission. Selecting the appropriate amount of redundant data can be achieved by applying RDO to this problem as well [53].

When transport protocols ensure delivery via packet retransmission the same mechanisms can cause delays and hence lower throughput. The network throughput can also fluctuate, causing jitter in the arrival time of the packets. This can result in difficulties for streaming of video as the decoder cannot wait for late video packets. Buffering is used to compensate for the effects of delay and jitter. However, in order to compensate for high variation in packet arrival time significantly large buffer is necessary. This imposes high memory requirements on the client but it also has a direct effect on QoE, because it increases the start-up time of the playback. This effect can be sometimes more damaging to QoE than lowering the bit-rate.

In this thesis we demonstrate a number of objective and subjective QoE measurement techniques applied on a limited range of factors. We have developed implementations on existing techniques and certain extensions where the state-of-the-art did not produce desired results. The results from these measurements deliver valuable information on the effects of these factors on QoE.

Nevertheless, in the effort to capture a fuller picture of the QoE of an operating multimedia system, it becomes evident that there are a large number of factors in play and there are an equally large number of parameters in the system that contribute to this factors. The relationship between the parameters, resources and technology in the system can be complex and highly non-linear [54]. So, there is a clear need to deal with this complexity and uncover the relationship between the system intricacies and the QoE [5].

1.5 Handling the Complexity of QoE Modelling

Our ambition is to create a framework for QoE-aware management of multimedia services. In order to do that we need to be able to understand how our management decisions are affecting the QoE. Yet, as QoE is multifaceted and has complex relationships with the available resources in the system, its modelling presents a challenge.

Many subjective studies of certain aspects of QoE (including our own) have been executed. Most of them are focused on the efficiency of the encoding [55], while others on the effects of specific errors on the quality. However, considering all the factors that affect quality in a subjective study would be an insurmountable task.

A more tractable way to deal with the multitude of factors that affect QoE is to use computational techniques. Computational intelligence and, more concretely, Machine Learning techniques offer the ability to correlate a vast amount of parameters with each output metric. They can discover complex interdependencies and detect non-obvious patterns. QoE models developed by combining objectively and subjectively measurable factors can deliver much better understanding of the delivered QoE to the viewer than by just looking at individual parameters such as bit-rate or video resolution.

In this thesis we present a system that collects a multitude of measurements from a multimedia system and correlates this information with subjective feedback from the users. The models delivered from the correlation can be further used to estimate the performance of the system over a longer period of time.

On-line learning techniques can be used to continuously adapt these models and deliver an accurate estimation of QoE, even in a continuously changing environment [56–58]. The understanding of QoE can deliver an efficient longer term management cycle of monitoring, evaluation and provisioning. Despite that, when faced with active control or short-term management decisions we need to understand the effect of each decision on the QoE. For this type of management instead of inference and modelling we need to move on to optimal control strategies.

In the following chapters we present description of a QoE management framework that addresses the challenge of complexity and adapts in an on-line fashion. We also present an approach of QoE-aware active control of multimedia systems, where short term decisions are made in correspondence with the fluctuations in the available resource.

1.6 Learning Versus Deterministic Design

Management of networked services typically means provisioning enough resources and allocating them appropriately. However, as certain resources are shared over the systems their availability varies over time. For many applications, making real-time decisions on the available resources makes the difference between delivering high quality service and failing to do so.

The usual approach in developing an efficient controller for real-time management is to design a suitable heuristic (or a rule based system) that will take appropriate decisions based on the state of the system. This approach requires a thorough understanding of the effects of the decisions on the performance of the system. As complexity in the system grows the design of efficient heuristics becomes more challenging and more expensive. As the system evolves rules become outdated [59].

In some areas, such as video encoding and video streaming RDO methods have been implemented to optimize the trade-off between quality and resources. Even though these methods have sufficient theoretical basis, practically the models that they rely on to calculate the rate and distortion do not fully capture the complexity of different video sources [45]. Furthermore, with the growth in the complexity of the systems, the interdependencies between the decision are not fully taken into account [60].

In contrast to this methodology, in this thesis we present an approach of ‘learning’ optimal strategies rather than ‘designing’ them. A computational intelligence technique based on reinforcement learning is used to discover the longer term utility of the decision, given the state of the system, and develop an optimal strategy.

This technique relies on previous techniques for modelling QoE and on well-established methods for reinforcement learning, offering an approach for designing system control that is scalable and adaptable to the changes in the environment.

1.7 Main Contributions

The focus of this work is developing methods for efficient management and control of delivered quality in multimedia services.

The main challenges facing this goal are understanding the different factors that affect the quality, the growing complexity in the interaction of those factors and the effect of the management decision on the quality.

In order to understand the delivered quality, we have defined QoE as its metric, discussed the factors that affected it and the resources that relate to these factors.

In Chap. 2 we continue to present a discussion on objective QoE methods and our implementations and developments of supporting techniques. Objective QoE methods are a cost effective way to measure the factors the contribute to the delivered quality. Their use is widespread, and they correlate in varying degree with the subjective QoE.

To understand the delivered QoE thoroughly, we turn to the subjective QoE methods in Chap. 3. This chapter presents a discussion on the existing subjective QoE methods and their drawbacks. Furthermore, it introduce a novel video subjective method based on psychometric evaluation that addresses many of these challenges.

Multimedia delivery systems are typically complex and their successful management requires a broader approach. In Chap. 4 we present our framework for QoE monitoring and provisioning that learns how to model all available measurements

into a QoE value. Moreover, we provide a solution for calculating the remedies in systems where the measured values are not satisfactory.

In following chapter (Chap. 5) we present our approach for real-time management or control of a multimedia system that infers the control logic based on the measured QoE.

The work on objective and subjective QoE models builds a basis for the QoE management and the QoE active control framework. These two frameworks offer a method for efficient management and control of the quality in multimedia services faced with growing complexity and continuous evolution of both the user expectations and the underlying technologies.

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