Perceptual Optimization of Large-Scale Wireless Video Networks

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1. Introduction

The next generation of video networks will deliver unicast and multicast of video content to mobile users, leveraging rapidly expanding wireless networks. Video networks must operate with high video network capacity, essentially maximizing the number of video flows that can be supported. Unfortunately, the application-agnostic paradigm of current data networks is not suited to meet rising video demands. Nor is the uniform coverage and capacity goal of cellular planning well suited for leveraging the spatio-temporal, bursty nature of video. We believe that video networks at every time-scale and layer should operate under the premise that distortion in the observed video stream, and in particular, perceptual distortion as would be perceived by a human consumer, should be the ultimate measure of error at the destination.

This paper summarizes key findings from a three-year project on video aware wireless networks with the objective of increasing (and defining a baseline) video capacity by at least 66x to meet projected capacity demands. Our research falls into two interconnected research vectors, summarized in Fig. 1. The work on video quality defined full-reference, reduced-reference, and no-reference models that achieve good correlation with subjective experiments. The models have been used to drive adaptation algorithms in the second research vector on spatio-temporal network adaptation. The work on network adaptation leverages aggressive deployment of small-cell infrastructure and exploits properties of stored-video streaming and real-time video to enable video-aware scheduling. The remainder of this letter summarizes select results in each research thrust.

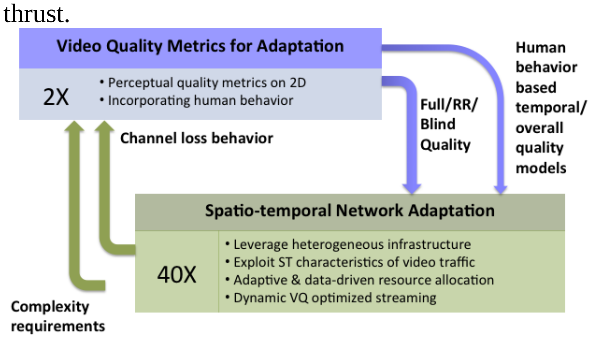

Fig. 3. Research directions and capacity gains.

2. Perceptual Video Quality Assessment

As discussed in a companion paper in this issue, a number of powerful new video quality assessment (VQA) models have been developed that deliver quality predictions that correlate closely with human quality judgments as measured on the Video Quality Expert Group (VQEG) FRTV Phase 1 database and on the LIVE VQA database [1]. The performance of these algorithms is boosted by the use of motion measurements [2] and/or natural video statistics, and depends on the amount of information available (if any) regarding the reference video(s) being tested. Efficacy is still high when little or no reference information is available; in particular "no reference" (NR) or blind models have great potential for assessing video traffic in wireless video networks.

Quality of Experience

Newly developed HTTP-based video streaming technology enables flexible rate-adaptation in varying channel conditions. The users' Quality of Experience (QoE) of rate-adaptive HTTP video streams, however, is not well understood. Therefore, designing QoE-optimized rate-adaptive video streaming algorithms remains a challenging task. An important aspect of understanding and modeling QoE is to be able to predict the up-to-the-moment subjective quality of video as it is played. In [3], we proposed a dynamic system model to predict the time-varying subjective quality (TVSQ) of rate-adaptive videos transported over HTTP. The new model effectively predicts the time-varying subjective quality of rate-adaptive videos in an online manner, making it possible to conduct QoE-optimized online rate-adaptation for HTTP-based video streaming. Fig. 2 shows that our dynamic system model can accurately predict the TVSQ.

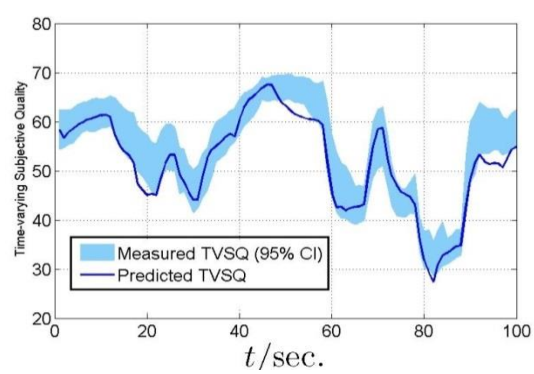

Fig. 2. The performance of the dynamic system model for TVSQ prediction.

A New Mobile Video Quality Database

Reference databases with mean opinion scores are important to allow researchers to compare competing VQA algorithms. We built a database of rate-varying video sequences called the LIVE Mobile Video Quality Database that simulate quality fluctuations commonly encountered in video streaming applications [4], [5]. We conducted a large scale subjective study on which time-varying subjective judgments of video quality were collected using two types/sizes of wireless display devices (smartphone and tablet). We envision that this free, publicly available database will prove useful for developing and validating visual quality models for quality-varying long videos.

3. Spatio Temporal Interference Management

Interference Shaping for Improved Quality of Experience for Real-Time Video Streaming

Bursty co-channel interference is a prominent cause of wireless throughput variability, which leads to annoying video quality variations. In [6], we propose and analyze a network-level resource management algorithm termed interference shaping to smooth video quality variations, by decreasing the peak rate of co-channel best effort users. The proposed algorithm is designed to maximize the H-MS-SSIM index [7], which incorporates a hysteresis (or 'recency') effect in predicting the perceived video quality. In Table I, we compare the performance of our IS method with a transmission scheme that does not incorporated IS. We utilized the coefficient of variation of Q (CoQV) defined by $\sqrt{Var[Q]}/E[Q]$ as a normalized measure of the fluctuation of the video quality. Table I reveals that our algorithm improves the average predicted quality with reduced predicted quality fluctuations.

Table I COMPARISON OF COQV AND AVERAGE MS-SSIM.

	Single Interference		Multiple Interference	
	CoQV	MS-SSIM	CoQV	MS-SSIM
Without IS	0.0694	0.9099	0.0119	0.9851
With IS	0.0097	0.9859	0.0076	0.9965

Multi-User Rate Adaptation for Stored Video Transport Over Wireless Systems

It has long been recognized that frequent video quality fluctuations could significantly degrade the QoE, even if the average video quality is high. In [8], we develop an online multi-user rate-adaptation algorithm (NOVA) to maximize the weighted sum of average quality and quality variations. The algorithm only requires minimal statistical information about the wireless channel dynamics and the rate-quality characteristics. For the wireless cellular downlink with fixed number of users, the algorithm is asymptotically optimal. Capacity gains with the proposed algorithm are in the range of 2x. In Fig. 3, we compare the performance of NOVA against that of PF-RM (which uses proportional fair resource allocation and buffer aware rate matching for quality adaptation) and PF-QNOVA (which uses proportional fair resource allocation and NOVA's quality adaptation) in a wireless network supporting N video clients. NOVA provides significant network capacity gains.

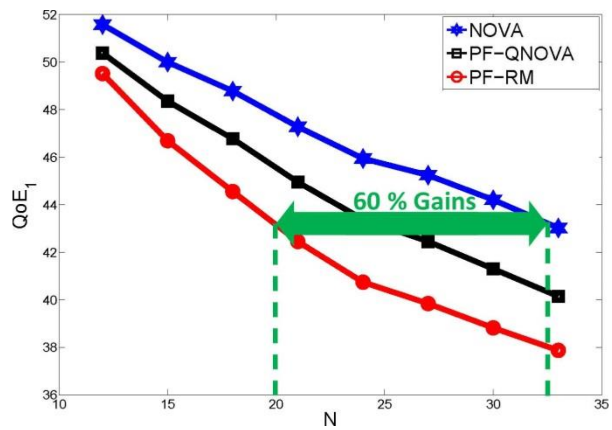

Fig. 3. The QoE (mean quality+variation) of NOVA.

MIMO Video Adaptation

In [11], we introduce an architecture for real-time video transmission over multiple-input multiple-output (MIMO) wireless communication systems using loss visibility side information of video packets. To jointly capture video quality and network throughput, we define the optimization objective as the throughput weighted by the loss visibility of each packet, a metric coined *perceived throughput*. We use the loss visibility side information to classify video packets and transmit them through different subchannels of the MIMO channel. When tested on H.264-encoded video sequences, the proposed architecture achieves the same video quality (SSIM [12]) at a 17 dB reduction in transmit power for a 2x2 MIMO system, giving a 2-4x capacity gain over a baseline MIMO system. Fig. 4 demonstrates the video quality gains achieved over a range of antennae. Our prioritized transmission methodology only requires an SNR of 3 dB to achieve a video quality of 0.9 on 2x2 MIMO systems. By comparison, the non-prioritized method requires 20 dB. Furthermore, gains in excess of 10 dB are achieved over a wide range of antenna configurations.

4. Conclusions

In this paper we summarized some of our recent work on developing new models for perceptual video quality assessment, and using these models to adapt video transmission based on perceptual distortion. Our adaptive algorithms give capacity gains on the order of 2-4x depending on the definition of capacity and the baseline. A major finding not discussed here is that capacity gains of 40x or more could be achieved through aggressive deployment of small-cell infrastructure [13]. These capacity gains come on top of the other gains from adaptive algorithms. In further work, we are developing models that better describe the quality of experience and using these models to develop more advanced algorithms.

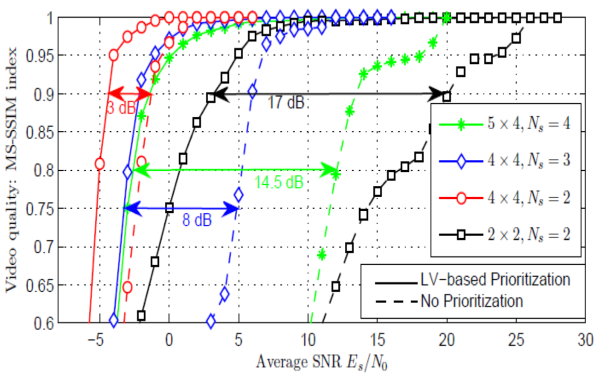

Fig. 4. Comparison of the loss visibility-based prioritization vs. non-prioritized MIMO precoding.

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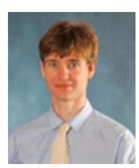
Al Bovik. See photo and biosketch in another letter in this issue.



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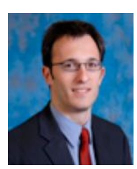

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