Project Proposal

CS 110

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1 Introduction

Recently, there has been a large shift towards video conferencing. While much research has been done over video streaming applications, relatively little has been done for video conferencing applications (VCA). In particular, some VCAs make it difficult to evaluate quality of experience (QoE) and quality of service (QoS) metrics from the network or even application layer. In particular; Zoom, a popular VCA controlling 76 % of the video-conferencing market as of June 2021 [1]; uses its own closed-source transport protocol [2] and only reports application performance at a minute's granularity [3]. This makes it difficult to evaluate QoE and QoS. Only by drawing relations between QoS and QoE metrics, we would be able to know more about possible ways we can further optimize the network and the experience of the users, when the network resources are limited, by updating the algorithms used by the programmable switches and servers.

1.1 Quality of Service

Quality of service (QoS) is a metric expressing the performance of the network. One important thing we need to know is packets: During the video meeting or video converancing through Internet, computers need to send and receive data. The data is packed into chunks, which we call it packets, and they are send through the rountes and into the Internet. The protocol most VCAs use is User Datagram Protocol (UDP), and its' packets do not contain any information about the network quality. Luckily, the application layer protocol, WebRTC, is able to note down some of the information while still very limited.

Due to the limited statistics we can collect from packet captures and the form of protocol VCAs are using, which is WebRTC under UDP, we can only collect several statistics for our project.

- Uplink bitrates

  Uplink bitrates or uplink capacity are the rate of the client sending packets to the other users or the relay server, usually measured in Mbps. Low uplink bitrates indicate that the user are not or unable to upload their videos and audios with great/clear quality.

- Downlink bitrates

Similarly, downlink bitrates or downlink capacity are the rate of the client downloading things from the other users or the relay server, also measured in Mbps. Low Downlink bitrates indicate users are not or not able to download the videos and audios of other users fast enough, or with great quality, which means the video might be low in resolution, refresh rates, or even lag or frezze.

- Packet loss

  Naturally, UDP does not collect information about packet loss, while the WebRTC, the application layer protocol that most of the VCAs use, are able to record packet loss information. It is imaginable that some packets will be loss on their way, probably due to bad network, congestions, or even broken cables. Recording packet loss can help us infer about the Quality of Experience of the users. Packet loss is measured in persentage in given period of time.

There are three major factors that contribute to poor video quality: packet loss due to unreliable transmission, delays caused by the network capacity, and jitter, caused by irregular delays [4].

1.2 Quality of Experience

Quality of experience (QoE) is the user's perception of QoS [4]. Because QoE is a subjective metric, it is typically measured using opinion surveys over experiment participants [4], [5]. Since the QoS metrics do not necessarily translate one-to-one to their perception of service quality, QoE has supplanted QoS as the barometer of user satisfaction [6].

While surveying users is an accurate measure of QoE, it is costly, not real-time, and only viable in a laboratory environment [4], [7]. Because of this, QoE must generally be modelled using the QoS metrics available to network operators. One such approach is that of Dinaki, Shirmohammadi, Janulewicz, *et al.* [6], who use a heuristic for video streaming QoE factoring the playback duration, join time buffering, buffering length, buffering frequency, and average bitrate. Song, Ge, Mahimkar, *et al.* [7] describe another QoE metric, Q-score. These systems use the QoS data in order to infer the user's QoE in real-time, allowing the network operator to make decisions on how to optimize the network performance.

Video conferencing in particular is impacted by QoS metrics such as the *frames per second* (FPS), *quantization parameter*, and the *video resolution* [8].

Quality of experience can be impaired by visual distortions. In video streaming, these distortions may include [9]:

- The *blocking effect*, where the reconstructed image contains block-shaped discontinuities due to the frame being encoded in blocks.
- *Blurring*, where the amount of detail in the image is lost, and the sharpness of edges is reduced.
- *Color bleeding*, where detail is smoothed out and areas with contrasting colors show smears of the other color.
- *Edginess*, where the edges of the image show distortions [4].

- *Jerkiness*, where “snapshots” of a continuous motion appear in succession, producing a “disjointed sequence”.

Quality of experience can also be negatively impacted by the format with which the video is compressed. When automatically monitoring for QoE, systems often consider the bitrate and the frame rate [4]. The bitrate is the rate at which the video codec compressing the video emits data, and the frame rate is the number of frames displayed per second. Moreover, the video itself may impact the QoE—videos with low amounts of movement may appear to have higher quality than videos with high amounts of movement when subjected to jitter or packet loss, for example [4].

1.3 WebRTC

WebRTC is an application-layer protocol used for video conferencing. It is built upon RTP. While some of the popular VCAs use WebRTC, Zoom uses its own closed-source extension [2], making it difficult to evaluate QoE and QoS metrics from the network layer. While the Zoom API does provide some QoE information, it is at a minute’s granularity [3], which is both at the application layer and is not fine enough for our purposes.

1.4 Applications

1.4.1 Proactive QoE Management

Real-time QoE monitoring can be used to improve the perceived QoE of users on the network. For example, the network may use the QoS parameters to proactively estimate the user’s QoE, and choose to reprioritize currently buffered packets in order to optimize said QoE [6].

2 Proposed Solution

In order to map quality of service to quality of experience for video conferencing applications, we intend to collect QoS data from the network and use statistics methods or even machine learning models to correlate it to QoE data obtained experimentally from devices.

The QoS data will be collected and mark with time stamps; the QoE, which is trickier, will be collected from the local machines. On the one hand, QoS data could be collected mainly through WebRTC. WebRTC provides us with very important data such as available bandwidth, resolution, and upstream/downstream datarates. By keeping track of WebRTC statistics and marking them with timestamp, we can later put the information together and see the relationship between these WebRTC data and the QoE data.

On the other hand, QoE is difficult to evaluate. Most VCAs do not provide QoE data to users and researchers. We will design a tool to capture useful QoE data from the client interface, marking it with timestamps for later processing. These data will include frame rate and change in frame rate.

3 Evaluation Plan

In order to evaluate our approach, we need to determine if we have collected enough and significant data that we can generalize our result to a greaeter scope. The first goal of our project is to ensure that we have reliable data that are significant enough for our research. By having a metric that keep track of the packet capture rate, we can imediately tell if there will be problems for the data we collected, when the capture rate drops.

The most important goal is to determine how well the trends of QoE data match with QoS data. The way we determine this would be general statistics methods, which analyze the relationship and relatability. By generating plots and graphs, we should be able to view the result very clearly.

We hope that our project is reproducible. Everybody can collect their own QoS and QoE data, given our model of collecting those data, and use their own AI/ML training models to achieve a similar result while customized for thier own network environment. For our result, we expect that the correlations generated by AI/ML trainings will not vary much over time, and the trained model should pass the test set generated using later collected data.

4 Timeline

- Fall 2021
  - *Weeks 1–6*
    - Read through related papers.
    - Develop a monitoring tool for watching machine statistics.
  - *Weeks 7–10*
    - Collect QoE and QoS data.
    - Find patterns in data.
- Winter 2022
- Spring 2022

References

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