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Adaptation Logic for HTTP Dynamic Adaptive Streaming using Geo-Predictive Crowdsourcing for Mobile Users

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Abstract The increasing demand for video streaming services with a high Quality of Experience (QoE) has prompted considerable research on client-side adaptation logic approaches. However, most algorithms use the client's previous download experience and do not use a crowd knowledge database generated by users of a professional service. We propose a new crowd algorithm that maximizes the QoE. We evaluate our algorithm against state-of-the-art algorithms on large, real-life, crowdsourcing datasets. There are six datasets, each of which contains samples of a single operator (T-Mobile, AT&T or Verizon) from a single road (I100 or I405). All measurements were from Android cellphones. The datasets were provided by WeFi LTD and are public for academic users. Our new algorithm outperforms all other methods in terms of QoE (eMOS).

Keywords Dynamic Adaptive Streaming over HTTP, Adaptic Logic, Crowdsourcing, Geo-Predictive

1 Introduction

Dynamic Adaptive Streaming over HTTP (DASH) [1] is the HTTP Adaptive Streaming (HAS) standard. It has recently been adopted by YouTube (Google) and Netflix. DASH splits a video into chunks and encodes each into several quality representations.

A client's DASH application often has a smart Adaptation Logic (AL) module. The AL module is responsible for selecting the most suitable quality representation to enhance the client's Quality of Experience (QoE) while considering factors such as the client's buffer and playback delay. QoE is affected by factors such as the number of quality changes and their sizes. There is a tradeoff between increasing the video quality and buffering additional video segments. A client's player often buffers a high number of segments to overcome network outages. Most current AL methods [2–10] estimate the next suitable segment based on estimates of previous segments without taking into account the future network characteristics. However, knowledge of geo-location network conditions can enable better decisions.

The term crowdsourcing was introduced by Howe [11] who defined crowdsourcing as the act of taking a task traditionally performed by a designated agent (such as an employee or a contractor) and outsourcing it by making an open call to an undefined but large group of people, especially from an online community.

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In the case of video adaptive streaming, crowdsourcing makes it possible to collect mobile network data anonymously and automatically. This is done using an application especially designed to improve the AL decision. Neidhardt et al. [12] reported that using many of the existing open datasets leads to low accuracy because of extreme outliers and few measurements for some of the cells. They noted that cellular location providers do not provide their complete data.

In this work, we present real-world, crowdsourcing datasets and test our proposed solution against state-of-the-art algorithms on them. Our work main goal is improving quality of experience while traveling without a known destination. We present six datasets, each of which contains samples of a single operator (T-Mobile, AT&T or Verizon) and from a single road (I100 or I405). All measurements were from Android cellphones of various users. The datasets were provided by WeFi LTD. The WeFi application collects granular information on mobile network performance and application usage from millions of devices, down to a 10×10 meter geographical resolution. The datasets are public for academic users [13].

There are also disadvantages to relying on a crowdsourcing service. For example, a crowdsourcing service might not be reliable or trustworthy. This problem may be mitigated by relying on a trusted and reliable cloud service such as Amazon Web Services (AWS).

We propose a Geo-Predictive Adaptive Logic (GPAL) algorithm based on crowdsourcing data and show that it outperforms the state-of-the-art: Riiser [14], MASERATI [15], n-Predict [16], 1-Predict [16], PBA [17], MAL [10] and MaxBW [2] algorithms. It is worth noting that our crowd sourcing data were generated by users of a large scale, professional service and not by simulation.

The remainder of this paper is organized as follows: Section 2 summarizes related work. Section 3 presents our crowd algorithm. Section 4 details our dataset characteristics. Section 5 describes the experimental setup and results. Section 6 discusses future work and conclusions.

2 Related Work

DASH AL is a well-investigated research topic. AL research can be roughly divided into two different groups: past estimate based AL and crowdsourcing based AL. Most work has investigated past estimate algorithms. Müller et al. [8] suggested a buffer based decision algorithm that uses the previous segment bandwidth estimates and the user's current buffer duration to select a suitable quality representation for downloading. The Multicast Adaptation Logic (MAL) algorithm [10] uses a double Exponential Moving Average (EMA) algorithm. One smooths the buffer size estimate and the other smooths the bandwidth estimate. This is done to select the most suitable segment. Although MAL was designed for multicast, it achieves good performance in unicast networks [10].

Crowdsourcing AL methods have attracted much less attention than past estimate based methods. Hung et al. [18] proposed a video streaming control mechanism based on location to overcome signal variations in train tunnels and underground areas. Geo-location frameworks that have the ability to predict future network conditions based on a *bandwidth lookup service* and similar concepts can be found in [19–22,16]. Acharya et al.[23] evaluated rate-adaptation in a vehicular network based on signal strength and throughput at a location as an indicator of congestion. Curcio et al. [19] and Singh et al. [20] suggested server-side prediction algorithms for RTP streaming. Curcio et al. [19] suggested a framework with a predictive server that obtains route, speed, location and throughput from the client. However, this study was based on simulation rather than real-world data. Singh et al. [20] proposed building a Network Coverage Map Service (NCMS) to make rate-control decisions over a Real Time Protocol (RTP) using a server-side adaptation algorithm. Singh et al. however did not investigate performance on datasets with a higher geographical coverage or more diverse network connectivity conditions.

Yao et al. [21] showed that past bandwidth information is a good indicator of the actual bandwidth at a given location. Yao et al. found that location had greater influence than time, based on traces. Nevertheless, their performance evaluation did not take into account the number of switches or the playout buffer size. Furthermore, it was gathered from a small set of vehicles.

Riiser et al. [22] proposed constantly monitoring the receiver's download rate and the associated GPS positional data to report a central database. This was argued to allow the user to better predict the near-future bandwidth availability and to create a video playout schedule based on the likely future availability bandwidth. The user bases his near future decision on the available bandwidth during the last interval to predict the available bandwidth during the next interval. The authors concluded that using past bandwidth lookups led to far fewer rebuffering events and stabler quality. Evensen et al.

[24] suggested using the geographical location information to predict available bandwidth accurately since the bandwidth is usually dependent on the user location. However, both systems [22,24] often lead to inaccurate bandwidth prediction or pay little attention to user environments (e.g., time, humidity, speed). Therefore, Han et al. [15] investigated the extent to which the available user mobile channel bandwidth was affected by constraints including location, time, speed, humidity and cellular network type (3G/4G). Their scheme, called MASERATI, outperformed Pure-DASH and LoDASH, where Pure-DASH (equivalent to [22]) only used the download throughput and LoDASH (equivalent to [24]) used location based bandwidth predictions as in [24,22].

Liu et al. [25] suggested comparing the segment fetch time with the media duration contained in the segment to detect congestion and probe the spare network capacity. Liu's algorithm used conservative step-wise up switching and aggressive down switching. Hao et al.[16] suggested two algorithms: 1-predict and n-predict. The 1-predict algorithm uses the playout buffer and the next prediction to determine the most suitable representation to download. The n-predict algorithm uses the average throughput of the next n time steps as the algorithm's current prediction. Hao et al. [16] evaluated Liu et al.'s algorithm and found that it achieved stable video quality but with a very low average bitrate. They showed that n-predict outperformed Liu et al's algorithm as well as 1-predict. Zou et al. [17] demonstrated that leveraging bandwidth predictions can significantly improve QoE. They designed an algorithm that combined bitrate prediction and rate stabilization. They showed that during startup, their algorithm had more than four times better video quality than heuristic-based algorithms.

Riiser et al. [14] recorded 3G mobile traces in Oslo, Norway, while traveling on different types of public transportation (metro, tram, train, bus and ferry). The traces, measured on the bus path between Ljan

Table 1 Comparison of Algorithms

Paper	Streaming Protocol	Idea	Trigger	Action	Quality Adjustment	Compared Algorithms	Observed Metrics
Singh et el. [20] - Geo-location Assisted Streaming System (GLASS) Rate-Switching	RTP/UDP + Temporal Maximum Media Stream Bit rate Request (TMMBR)	Avoiding buffer underrun - client looks ahead at locations in its vicinity for bad coverage	Future Coverage Hole	Client Pre-Buffer	Client media rate switch according to available throughput in the coverage hole	No adaptation (RTCP), rate switching GLASS, late scheduling GLASS, Omniscient (Optimal)	packet loss rate, average receive rate, Y component of the PSNR, throughput
Yao et al. [21] - BW-MAP-TFRC	adaptive TCP streaming with TCP Friendly Rate Control (TFRC) [26]	Avoiding packet loss - client updates the server when it changes its location. The server determines the average bandwidth at that location in the past	Location changed by client followed by a new BW value	Server changes its sending rate	Short freezing of the TFRC and disabling the normal operation of TFRC when needed	TFRC and BW-MAP-TFRC	estimated Mean Opinion Score [27], Peak Signal-to-Noise Ratio (PSNR), Glitch (Drop in the streaming quality)
Riiser et al. [22]	Apple Live HTTP	Minimizing rapid fluctuations in quality and avoiding buffer underrun - client's estimate of the number of bytes that it can download during the remaining time of the trip	Client receives a sequence of bandwidth averages for its whole path	Client plans which quality levels to use	Apple Live HTTP mechanism	Buffer-Based Reactive, History-Based Prediction, Omniscient Prediction (Optimal)	Buffer size, selected representations
Han et al. [15] - MASERATI	DASH	Avoiding frequent or large video quality changes	The algorithm finds the most similar database entry and estimates the available bandwidth	The bit rate of the next video segment is defined by that bandwidth	DASH Adaptation mechanism	Pure-DASH, Location-based DASH (LoDASH) [22], MASERATI	Playout Success Rate, Quality of Segments, Frequency of Quality Changes, Degree of Changed Quality Level
Hao et al.[16] - 1-predict, n-predict	DASH	Achieving continuous playback - DASH Based algorithm with an additional function to anticipate future path and bandwidth, and to determine the predicted rate	The server calculates the possible bandwidth and sends it to the client	DASH Client applies the best quality level it can afford	DASH Adaptation mechanism	Liu et al. [25], Adobes Open Source Media Framework (OSMF), 1-Predict, N-Predict	Segment representation Level, Ratio of bandwidth utilization, rate of video quality level shift
Zou et al. [17] - PBA	DASH	Avoiding stalls, preserving stability while maintaining improved average quality - the client decides which quality to pick using the buffer state and the quality of historical chunks	Buffer occupancy changes all the time during download	Client can decide when to download any quality level	DASH	FESTIVE [28] , BBA [29], optimal(mixed integer linear programing), PBA	Average quality rate supplied in the first 360s/32s, Number of stalls, Number of switches

and Oslo central station, Norway, had a total duration of about 220 minutes (almost 12500 samples). The available bandwidth was between 202bps and 6335kbps with an average of 2192kbps and STD of 1317kbps. This dataset has been used in several papers such as [30]. For our crowd sourcing algorithm we needed a bigger dataset both for the entire road and for every part of the road. Moreover, we had samples from different days of the week and various mobile devices. Therefore, we decided to only use our dataset. Note that, our Dummynet server (see Section 5.2) was equivalent to the Apache server in [14] so as to produce the same network conditions for all tests. Table 1 summarizes the papers presented above.

3 The Geo-Predictive Adaptive Logic (GPAL) Algorithm

We define the user playout buffer as $B(t)$. The goal of the AL modules is to maximize the overall quality of the stream, while eliminating rebuffering ($B(t) > 0$). We measure the quality in terms of its eMOS score [31,32] as can be seen in Eq. 1.

$$\begin{aligned} \text{eMOS} &= \max\left(0.81\mu - 0.96\sigma - 4.95\phi + 0.17,\ 0\right) \\ \phi &= \frac{7\max\left(\frac{\ln(F_{freq})}{6} + 1,\ 0\right) + \frac{\min(F_{avg},\ 15)}{15}}{8} \end{aligned} \tag{1}$$

The eMOS combines the re-buffering effect on the users experience with the influence of the selected quality representation (for more information see [31]). The eMOS range is between 0 to 5.84 (the highest quality). In these equations F_{freq} and F_{avg} represent the number of re-buffering events relative to the number of segments and the average duration over all re-buffering, respectively. The quality effect on the user is expressed as (μ) the normalized average quality level and the (σ) the standard deviation of the normalized quality level. Note that eMOS[31,32] is an estimated MOS based on several video parameters such as quality and re-buffering. In our model, we used an estimated Mean Opinion Score (eMOS) formula (Eq. 1) based on the work of Claeys et al. [31].

Finally, our algorithm tries to maximize the eMOS subject to constrains as shown in Eq. 2.

$$\begin{aligned} &\max(\text{eMOS}) \quad s.t: \\ &\forall t > t_{start} \quad 0 < B(t) \leq B_{max} \end{aligned} \tag{2}$$

The GPAL algorithm, Algorithm 1, determines the representation of the next media segment to be fetched. The algorithm estimates the current segment download path based on the client's location and speed. It predicts the future path network bandwidth conditions based on the client's playout buffer and the crowd estimated bandwidth. The algorithm calculates the playout buffer fullness ratio (B_p) based on the maximum between the current buffer levels divided by the maximum buffer size allocation. The bandwidth coefficients (thresholds) in our algorithm are taken from MaxBW [2].

4 Dataset

The WeFi datasets contain samples from the California I110 and I405 interstates. The I110 is an interstate highway in the Los Angeles area and connects San Pedro and the port of Los Angeles with downtown Los Angeles and Pasadena. The I405 is a major north-south interstate highway in Southern California. Table 2 summarizes the number of samples on each road over a operator.

Each sample of the dataset contains *longitude*, *latitude*, *data throughput* and *data size*. A large number of different applications generated the data. Most of the applications either regularly send low rate

Table 2 Number of samples of operator users on a road

	I110	I405
T-Mobile	40667	61516
AT&T	20312	45028
Verizon	22032	38448

Algorithm 1 GPAL: Geo Predictive Adaptation Logic Algorithm

g: current mobile geo-location.
v: current mobile speed.
w: highest quality average file size.
f: last downloaded segment throughput estimate.
$X_{bw}(t)$: bandwidth estimate for the current time (t).
ρ: predicted mobile bandwidth for next segment.
$B(t)$: current playout buffer duration.
B_p: playout buffer fullness ratio.
B_{max}: maximum buffer size.
τ: selected quality for download.
$B_p = \frac{B(t)}{B_{max}}$
if first segment **then**
    $B_p = 0.5$
end if
$segLen = \begin{cases} 250m & \text{if first segment} \\ v\frac{w}{f} & \text{else} \end{cases}$
newRegion = circle whose middle point is g and its radius is *segLen*
$X_{bw}(t)$ = getCrowdBWAverage(*newRegion*)
if $B_p < 0.2$ **then**
    $\rho = 0.3X_{bw}(t)$
else if $B_p < 0.4$ **then**
    $\rho = 0.5X_{bw}(t)$
else if $B_p < 0.55$ **then**
    $\rho = X_{bw}(t)$
else
    $\rho = (1 + 0.5B_p)X_{bw}(t)$
end if
τ = the highest bit rate representation for which $\tau < \rho$
return τ

updates or are in the idle state (sending keep-alive messages). Thus, most of the samples' *data throughput* are significantly lower than the real *channel throughput*. Thus, for each road interval x we estimate its *channel throughput*, E_x, using Eq 3.

$$E_x = \frac{\sum_{s \in x} D_s \cdot A_s}{\sum_{s \in x} D_s} \tag{3}$$

where D_s is sample s' *data size* and A_s is sample s' *data throughput*. This estimate gives more weight to high *data throughput* as there are more data transmitted in high *data throughput*. It is noteworthy that practically all samples of long-duration TCP connections are the ones that are used almost exclusively for the estimation of the absolute throughput. WeFi used our equation and verified experimentally that the estimate is accurate. Figs. 1-2 depict *data throughputs* vs. estimated *channel throughputs* along the roads (for 12 meter segments). We can see that the estimated *channel throughput* varies along the roads and are high enough for video streaming in different video quality representations. The dataset was split into the different operators. Then, each of these datasets was split into a train set and a test set. The train set contained samples from Wednesday, Thursday, Friday and Saturday. The test set contained samples from Sunday, Monday and Tuesday. The train sets were used as the crowd source data and the test sets were used for bandwidth generation using the testing phase via Dummynet [33].

4.1 Interstate I110

The interstate heat map is illustrated in Fig. 3(a) which shows that the road throughput can vary between $0.5 - 5[Mb/s]$. Fig. 3(b) depicts the measured bandwidth of the path (average and STD). We define this bandwidth path as I110.

The median throughput of the interstate is $0.86[Mb/s]$, the average throughput is $1.585[Mb/s]$ and the STD is 2. That is, the path has many fluctuations. Thus, it is challenging for adaptive streaming clients to adapt to its network conditions.

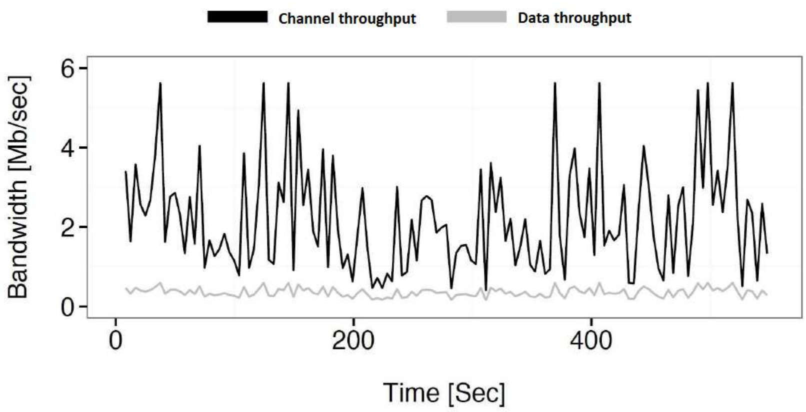


Fig. 1 I110 channel throughput (E_x) *vs.* data throughput (A_s)

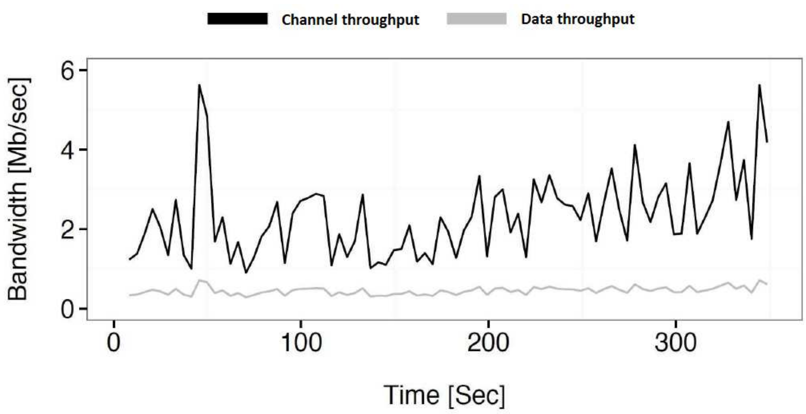


Fig. 2 I405 channel throughput (E_x) *vs.* data throughput (A_s)

Fig. 3(c) depicts the throughput density and the sample densities along the route. We split the throughput density into fixed bins from 0 to the maximum observed throughput, $10[Mb/s]$. It is clear that lower throughput in the ranges of $0 - 2[Mb/s]$ are more likely while throughput above $5[Mb/s]$ are less common. Fig. 3(d) shows the sample densities along the route. From $23km$ the sample densities decrease.

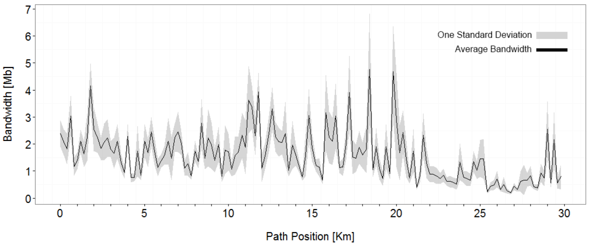
4.2 Interstate I405

The I405 interstate is shorter but has a higher number of samples than the I110 interstate (see Table 2). The interstate heat map is illustrated in Fig. 4(a) which shows that the road throughput varies between $0.5 - 5[Mb/s]$. Fig. 4(b) depicts the measured bandwidth of the path (average and STD). We define this bandwidth path as $I405A$.

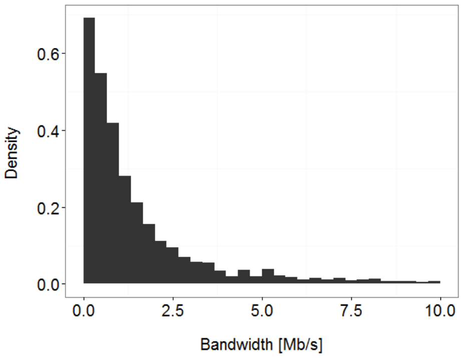
The median throughput of the interstate is $1.97[Mb/s]$, the average throughput is $2.63[Mb/s]$ and the STD is 2.15. The I405 interstate has a higher throughput average than I110. The STD is slightly higher.

Fig. 4(c) illustrates the throughput density and the sample densities along the route. We split the throughput density into fixed bins from 0 to the maximum observed throughput $10[Mb/s]$. The table shows that the I405 throughput density is different from the I110 throughput density and the throughput is better spread between $0.5 - 2.5[Mb/s]$. Fig. 4(d) depicts the density of the samples along the route.

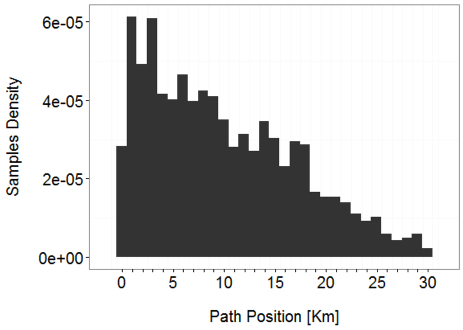
(a) I110 throughput heat map



(b) I110 path positioning

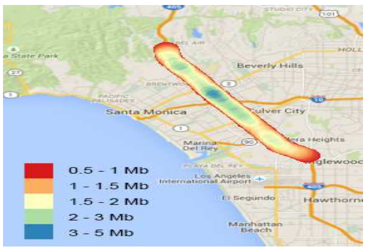


(c) Bandwidth entropy (PMF) analysis

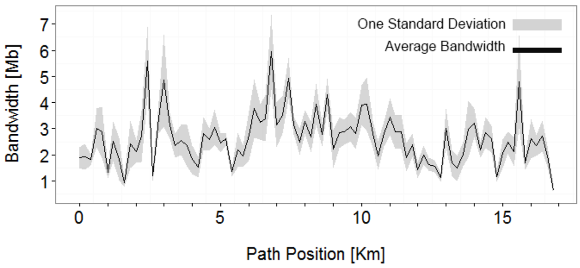


(d) Samples' density entropy (PMF) analysis

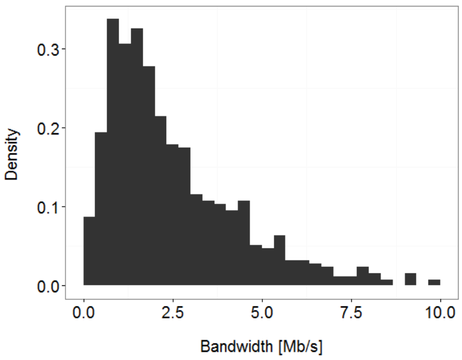
Fig. 3 Interstate I110 dataset detailed depiction.



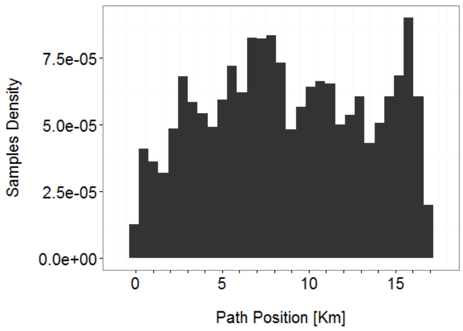
(a) I405 throughput heat map.



(b) I405 path positioning



(c) Bandwidth entropy (PMF) analysis



(d) Samples' density entropy (PMF) analysis

Fig. 4 Interstate I405 dataset detailed depiction.

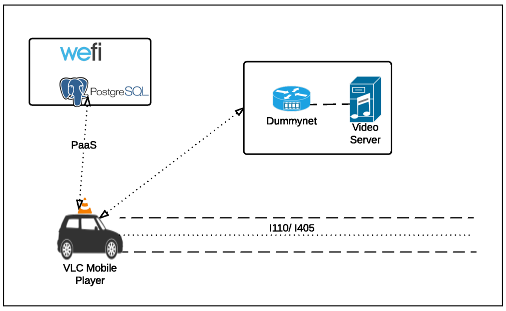


Fig. 5 Experimental setup diagram

5 Experiments and Results

We describe our experimental setup and video representation information in Section 5.1. We discuss our experimental results in Section 5.2.

5.1 Experimental Setup

This section describes our experimental settings and video encoding configuration. We used the Big Buck Bunny (BBB) [34] video encoded into fixed duration segments of 2 seconds. Table 3 illustrates the BBB available representation stored in the streaming server. The client playout buffer duration was set to 30 seconds.

Representation	SSIM	PSNR $[dB]$	Average bit rate $[Kb/s]$	Resolution	Average QP
50	0.719	24.4	51.05	320×240	50.82
100	0.800	28.3	98.91	320×240	44.13
200	0.890	32.4	193.31	480×320	35.60
250	0.914	34.0	240.96	480×320	33.23
500	0.960	38.0	480.15	854×480	27.01
750	0.971	40.0	721.56	854×480	23.61
1000	0.977	41.4	964.16	854×480	21.29
1500	0.985	43.3	1452.44	1200×720	18.06
2000	0.988	44.5	1942.40	1200×720	15.81
2400	0.989	45.3	2335.20	1200×720	14.40

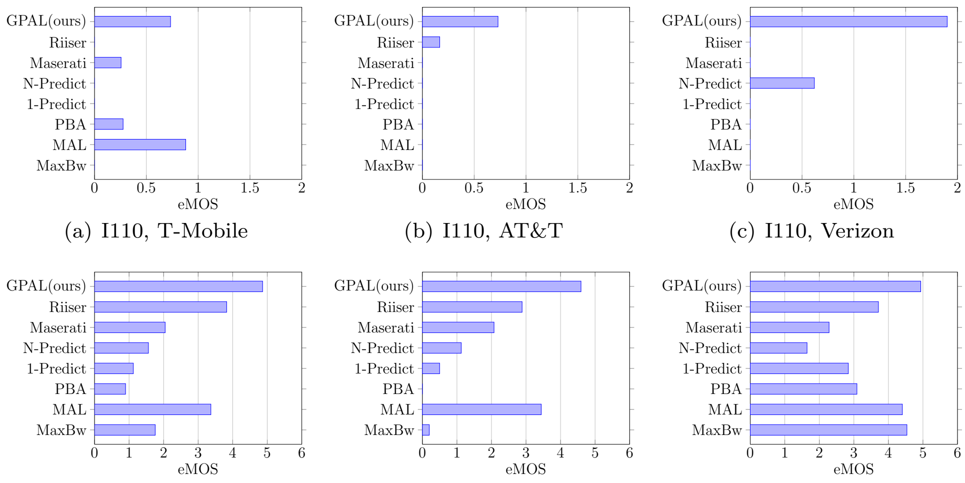
Table 3 Big Buck Bunny representation information. SSIM and PSNR were computed between the original high quality resolution and the lower quality representations after upsampling them to the same high resolution.

Fig. 5 illustrates our experimental setup. First, the user requests (using VLC [35]) the video MPD file from the HTTP server via the Dummynet [33] which shapes the traffic. The Dummynet network scenario does not use any information from the train dataset (Wednesday, Thursday, Friday and Saturday). The Dummynet network scenario is based on the test dataset (Sunday, Monday and Tuesday).

After the client receives it, the adaptation logic algorithm requests the crowd estimate from the PostgreSQL geo-predictive server (taken from the train set). Then, the user sends a request to the server using a simple API implementation which only sends the following information to the server: the search radius (250 meters), the user's current location and the estimated end point (which depends on the user's average speed). The geo-predictive module predicts the average throughput. Since this API is very lightweight, the process delay is negligible.

We do not assume we know the route. Therefore, we used a batch fetching mechanism. That is, before the current segment download ends, we fetch the crowd estimate for the next segment. Each adaptation logic can analyze the data or use the API differently but the fetching optimization is beyond the scope of this study. As a result, the segment download is delayed according to the network conditions.

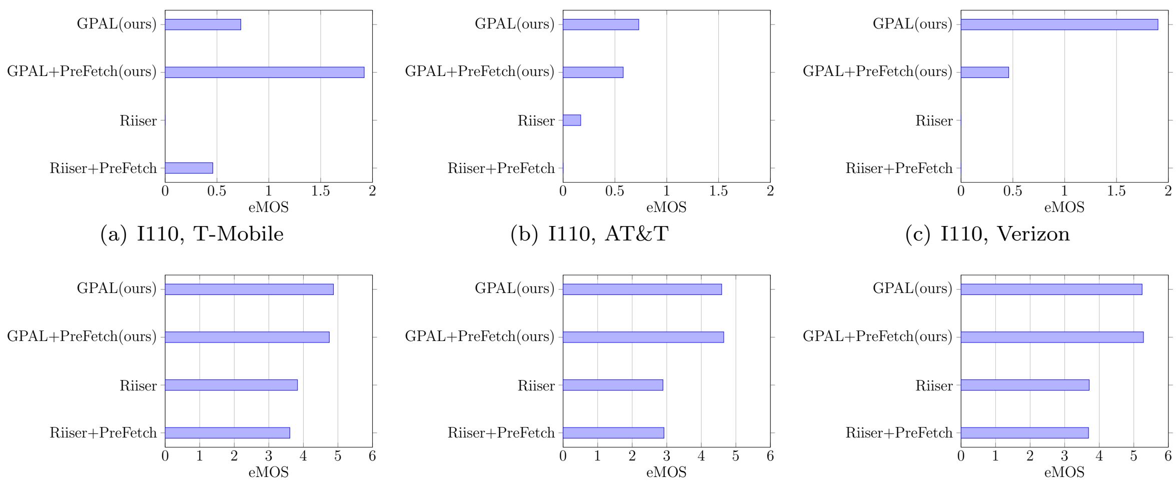
In order to compare our work to state-of-the-art algorithms we used the same segment fetching schema as these works, where the client downloads each segment one after the other.



(a) I110, T-Mobile (b) I110, AT&T (c) I110, Verizon

(d) I405, T-Mobile (e) I405, AT&T (f) I405, Verizon

Fig. 6 eMOS results for the different datasets. The new algorithm, GPAL, has the best performance for all datasets except I110, T-Mobile, where it was slightly outperformed by MAL.



(a) I110, T-Mobile (b) I110, AT&T (c) I110, Verizon

(d) I405, T-Mobile (e) I405, AT&T (f) I405, Verizon

Fig. 7 Comparison of GPAL and Riiser algorithms with and without prefetching mechanism. Prefetching did not improve eMOS results in most cases and even lowered it in some cases.

5.2 Experimental Results

In Eq. 2 we stated our goal. In our experiments B_{max} was 30 seconds. All the algorithms implemented the constraints in Eq. 2.

Fig 6 depicts the eMOS score (Eq. 1) for all the algorithms. Our algorithm, GPAL, has the best performance for all datasets except I110 over T-Mobile, where it was slightly outperformed by MAL. MAL and Riiser also exhibited good performance. We can see several cases where the eMOS score is zero. This is especially noticeable on I110 road over AT&T and Verizon operators where the cellular network conditions were hard.

Our main goal was to improve the quality of experience while traveling without a known destination. Additionally, we tested the performance of a prefetch mechanism. We added planning inspired by the ideas of [22]. Based on the user's speed, we estimated the user's location on the road of the next segment request. The adaptation logic algorithm decides the qualities both for the current segment and the next segment and requests the average quality for the current location. We tested this method using both our GPAL algorithm and the Riiser algorithm. The results are presented in Fig. 7. Prefetching did not improve eMOS results in most cases and even lowered it in some cases.

Table 4 T-Mobile user results, over road I110

Algorithm	Average bitrate [Kbps]	eMOS	Average PSNR	Num of Buffering	Num of Switch Up	Num of Switch Down	Sum: up + down	μ	σ	ϕ
GPAL	236.55	0.73	33.26	4.00	32.00	32.00	64.00	3.64	**0.89**	0.30
Riiser	125.56	0.00	28.89	4.00	10.00	9.00	19.00	2.22	1.01	0.31
Maserati	238.05	0.26	32.66	4.00	42.00	47.00	89.00	3.45	1.23	0.31
N-Predict	95.41	0.00	27.04	4.00	**6.00**	6.00	12.00	1.73	1.01	0.31
1-Predict	**624.22**	0.00	36.70	20.00	49.00	31.00	80.00	5.04	2.25	0.54
PBA	576.11	0.28	**37.58**	20.00	38.00	24.00	62.00	**5.26**	1.52	0.54
MAL	407.71	**0.88**	35.47	**3.00**	9.00	**2.00**	**11.00**	4.35	1.55	**0.27**
MaxBw	604.04	0.00	36.71	12.00	69.00	67.00	136.00	5.07	2.10	0.47

Table 5 AT&T user results, over road I110

Algorithm	Average bitrate [Kbps]	eMOS	Average PSNR	Num of Buffering	Num of Switch Up	Num of Switch Down	Sum: up + down	μ	σ	ϕ
GPAL	243.98	**0.73**	33.35	**4.00**	25.00	22.00	47.00	3.70	**0.95**	**0.31**
Riiser	150.24	0.17	30.50	**4.00**	16.00	10.00	26.00	2.88	1.13	0.41
Maserati	172.32	0.00	29.28	12.00	33.00	37.00	70.00	2.44	1.6	0.47
N-Predict	150.91	0.00	28.86	**4.00**	**3.00**	**5.00**	**8.00**	2.33	1.52	0.31
1-Predict	385.92	0.00	32.48	28.00	45.00	25.00	70.00	3.62	2.4	0.59
PBA	**424.91**	0.00	**34.42**	28.00	34.00	23.00	57.00	**4.15**	2.04	0.60
MAL	308.73	0.00	33.24	16.00	20.00	15.00	35.00	3.70	1.68	0.51
MaxBw	404.14	0.00	32.53	8.00	60.00	53.00	113.00	3.65	2.49	0.41

Table 6 Verizon user results, over road I110

Algorithm	Average bitrate [Kbps]	eMOS	Average PSNR	Num of Buffering	Num of Switch Up	Num of Switch Down	Sum: up + down	μ	σ	ϕ
GPAL	216.77	**1.90**	32.47	**0.00**	51.00	47.00	98.00	3.37	**1.04**	**0.00**
Riiser	191.93	0.00	30.10	95.00	18.00	13.00	31.00	2.51	1.23	0.31
Maserati	285.49	0.00	31.81	12.00	47.00	60.00	107.00	3.27	1.93	0.47
N-Predict	140.40	0.62	28.57	**0.00**	**7.00**	**11.00**	**18.00**	2.19	1.38	**0.00**
1-Predict	336.25	0.00	**32.91**	32.00	40.00	31.00	71.00	**3.63**	1.97	0.61
PBA	**388.29**	0.00	32.61	152.00	40.00	24.00	64.00	3.62	2.36	0.84
MAL	238.07	0.00	30.94	14.00	27.00	13.00	40.00	2.93	1.73	0.50
MaxBw	231.58	0.00	30.93	12.00	52.00	50.00	102.00	2.97	1.75	0.47

Table 7 T-Mobile user results, over road I405

Algorithm	Average bitrate [Kbps]	eMOS	Average PSNR	Num of Buffering	Num of Switch Up	Num of Switch Down	Sum: up + down	μ	σ	ϕ
GPAL	1041.39	**4.87**	**41.40**	**0.00**	33.00	30.00	63.00	**7.0**	**1.01**	**0.00**
Riiser	807.20	3.83	39.70	**0.00**	16.00	10.00	26.00	6.21	1.43	**0.00**
Maserati	423.36	2.04	35.12	**0.00**	42.00	53.00	95.00	4.38	1.75	**0.00**
N-Predict	233.63	1.56	32.30	**0.00**	**9.00**	**6.00**	**15.00**	3.28	1.32	**0.00**
1-Predict	**1171.55**	1.12	39.98	8.00	49.00	34.00	83.00	6.80	2.63	0.41
PBA	1113.43	0.90	40.66	24.00	36.00	25.00	61.00	6.80	2.04	0.57
MAL	887.93	3.37	39.48	**0.00**	14.00	7.00	21.00	6.23	1.93	**0.00**
MaxBw	1115.30	1.76	40.08	4.00	66.00	61.00	127.00	6.70	2.40	0.31

Table 8 AT&T user results, over road I405

Algorithm	Average bitrate [Kbps]	eMOS	Average PSNR	Num of Buffering	Num of Switch Up	Num of Switch Down	Sum: up + down	μ	σ	ϕ
GPAL	950.13	**4.59**	**40.94**	**0.00**	26.00	22.00	48.00	6.72	**1.06**	**0.00**
Riiser	693.47	2.89	38.20	**0.00**	17.00	12.00	29.00	5.58	1.88	**0.00**
Maserati	416.03	2.07	35.17	**0.00**	45.00	52.00	97.00	4.36	1.69	**0.00**
N-Predict	190.91	1.12	30.76	**0.00**	**6.00**	**6.00**	**12.00**	2.96	1.50	**0.00**
1-Predict	1010.36	0.50	39.12	11.00	48.00	29.00	77.00	6.29	2.61	0.46
PBA	1231.16	0.02	40.31	44.00	40.00	25.00	65.00	**6.88**	2.11	0.71
MAL	790.96	3.44	39.14	**0.00**	13.00	7.00	20.00	6.03	1.68	**0.00**
MaxBw	**1013.60**	0.20	39.05	16.00	59.00	52.00	111.00	6.28	2.63	0.51

Table 9 Verizon user results, over road I405

Algorithm	Average bitrate [Kbps]	eMOS	Average PSNR	Num of Buffering	Num of Switch Up	Num of Switch Down	Sum: up + down	μ	σ	ϕ
GPAL	1240.38	**5.24**	42.23	**0.00**	36.00	29.00	65.00	7.47	**1.02**	**0.00**
Riiser	853.99	3.71	39.79	**0.00**	15.00	10.00	25.00	6.27	1.60	**0.00**
Maserati	521.64	2.28	36.25	**0.00**	59.00	68.00	127.00	4.81	1.85	**0.00**
N-Predict	324.58	1.64	33.60	**0.00**	13.00	10.00	23.00	3.79	1.67	**0.00**
1-Predict	**1504.06**	2.84	42.09	4.00	38.00	24.00	62.00	7.85	2.25	0.31
PBA	1498.48	3.09	**43.08**	16.00	34.00	26.00	60.00	8.04	1.10	0.51
MAL	1124.72	4.40	41.25	**0.00**	**8.00**	**0.00**	**8.00**	7.05	1.53	**0.00**
MaxBw	1490.58	4.54	42.26	**0.00**	60.00	52.00	112.00	**7.87**	2.10	0.00

Tables 4-9 present the detailed numerical results of our experiments. For each evaluation metric, the best algorithm's results (highest for average bitrate, eMOS, PSNR, μ and lowest for all the others) are marked in bold. We can see that in many cases algorithms had very good results in one metric at the cost of having very low results in another metric, thus achieving an overall low quality of experience. For example, 1-Predict, PBA and MaxBw PSNR and average bitrate results were excellent. However, they had a high number of rebuffering events and relatively high number of switches which reduced the eMOS scores to low values, especially on the I110 road. Maserati and MaxBW had a high number of switches and their other QoE parameters were not especially good and thus the overall eMOS scores were low. Riiser and MAL algorithms had good performance, where the QoE parameters were relatively balanced. Finally, GPAL had the least number of buffering events (except on I110 over T-Mobile where it was 2nd best). Additionally, GPAL had balanced all other QoE parameters and thus its QoE was the best.

6 Conclusion

We proposed a new crowd-based algorithm called GPAL. We evaluated our algorithm and state-of-the-art algorithms on large, real-life, crowdsourcing datasets. Our algorithm, GPAL, outperformed all other state-of-the-art algorithms. Thus an optimal adaptation logic should estimate the distance between the current conditions and the cloud conditions. Our future work will aim at designing an adaptation algorithm that can leverage the advantages of past download algorithms with crowd knowledge based on the conclusions drawn from this work. An interesting approach would be to implement machine learning algorithms (similar to Claeys et al. [31]) combined with crowd data. Another possible direction would be to harness a client-side pre-fetch and HTTP2 server-side push mechanism based on crowd knowledge similar to [36–41].

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