MASERATI: Mobile Adaptive Streaming based on Environmental and Contextual Information

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ABSTRACT

Wireless/mobile video streaming has become increasingly popular, which makes wireless link bandwidth scarce. To provide streaming services to mobile users, it is crucial to adapt to the link condition and traffic fluctuation. We investigate which factors in natural environments and user contexts affect the available link bandwidth. To this end, we conduct a measurement study which contains 38 repeated trips along the same 5 km circular road in the campus of Seoul National University in April and May 2013. We measure the download throughput of video streaming from two different networks (3G and 4G LTE) with varying location, time, humidity, and speed. Our measurement results reveal that the humidity and location are the more important factors in the 3G network, while the speed, time, and location are the more important ones in the 4G LTE network to predict the available link bandwidth. We then propose an adaptive video streaming framework, MASERATI, where the information of environments and contexts is used to predict the available bandwidth. We demonstrate that MASERATI significantly improves the QoE of mobile streaming users in terms of the playout success rate, video quality, and stability, in comparison to DASH.

Categories and Subject Descriptors

C.2.1 [**Network Architecture and Design**]: Wireless communication

General Terms

Experimentation, Measurement, Performance, Reliability

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Keywords

Measurement; Video streaming; Adaptive streaming; Entropy; Bandwidth prediction; Bitrate planning; Mobile computing; Wireless; 3G; 4G

1. INTRODUCTION

According to the Cisco VNI report in 2012 [2], the largest portion of the mobile data traffic is video streaming, which is expected to account for over two thirds of all the mobile data traffic in 2015. To provide stable (or not disruptive) video streaming services to mobile users, adapting the rate of video traffic to varying resource availability and/or network condition is crucial [3, 8, 10]. That is, the fluctuation of link bandwidth is the major hurdle in offering video streaming services [13].

To address this issue, the idea of adjusting the bit rate of video traffic depending on the (time-varying) available bandwidth has been proposed, called adaptive streaming technologies [9, 11, 15, 17]. Many popular HTTP adaptive streaming services such as Apple's HTTP Live Streaming [9] and Microsoft's Smooth Streaming [17] are on the market, and traditional streaming services such as YouTube [11] have adopted the adaptive approach as well. Recently, the MPEG group has also standardized Dynamic Adaptive Streaming over HTTP (DASH) [15]. The basic idea of DASH is to let an HTTP media server divide a video file into a number of segments, each of which can be encoded with multiple quality levels, and to make a client request the appropriate quality of video segment for each interval depending on her/his varying link bandwidth.

However, these solutions mostly rely on the information of the available link/path bandwidth during the latest time interval to predict the available bandwidth during the next interval, which often leads to inaccurate bandwidth prediction [4]. For example, if a user is about to move into a tunnel, the expected available bandwidth will be substantially low, but the above solutions often fail to predict this situation.

Predicting the available bandwidth accurately is important for better quality of experience (QoE) in video streaming [6] since the video quality changing too often or too severely will negatively affect a user's perception [7, 18]. To address this problem, [4, 12] have suggested to use the geographical location information to predict available bandwidth accurately since the bandwidth is usually dependent on the location [16].

While these studies reveal valuable insights into predicting available bandwidth with the location information for adaptive video streaming, there has been little attention to the information of environments and user contexts (e.g., time, humidity, speed). For example, given a particular location, the expected bandwidth at the location may be different at 6 am and at 3 pm since the number of users at each moment is likely to be different. To understand the bandwidth predictability in mobile environments, we thoroughly investigate what factors affect the available bandwidth, not to mention location. To this end, we have conducted a measurement study which contains 38 repeated trips along the same 5 km circular road in the campus of Seoul National University in April and May 2013. We have measured the download throughput of video streaming from two wireless networks: 3G and 4G LTE. We investigate and analyze various factors including the location, time, humidity, and mobile speed.

Based on the analysis, we propose MASERATI which relies on the above factors to predict the available bandwidth. MASERATI estimates the available bandwidth based on the environmental and contextual information as well as the latest download throughput, and decides the bit rate of video streaming for the next interval.

The main contributions of this paper are three-fold:

1. To the best of our knowledge, this is the first measurement study to investigate which factors (location, time, humidity, speed, and network type) affect the available bandwidth in 3G and 4G LTE networks.

2. We find that the humidity and location are the more important factors in the 3G network, while the mobile speed, time, and location are the more important ones in the 4G LTE network to predict the available bandwidth.

3. We propose MASERATI where the environmental and contextual information is comprehensively used to predict the available bandwidth. MASERATI significantly improves the QoE of mobile streaming users in terms of the playout success rate, quality of segments, quality change frequency, and degree of quality change, in comparison to DASH.

The remainder of this paper is organized as follows. After describing the measurement methodology in Section 2, we analyze what factors affect the available bandwidth in Section 3. We then propose and evaluate MASERATI in Sections 4 and 5, respectively. We finally conclude with future work in Section 6.

2. MEASUREMENT METHODOLOGY

To investigate what factors (e.g., location, time, speed, humidity) of a mobile user have an impact on the available link bandwidth, we have conducted a measurement study which includes 38 repeated trips along the same 5 km circular road at Seoul National University (SNU) in April and May 2013. Figure 1 illustrates the trajectory of our measurements. Each trip has the same start point, end point, and direction.

Figure 1: The trajectory of our measurements in the campus of Seoul National University is shown, which is about 5 km long.

We have measured the download throughput of video streaming from two wireless networks: 3G and 4G LTE. We use an Android-based smart phone (KTTech EM-100), which supports both 3G and 4G LTE. Note that we use data services through KT, a mobile operator that provides both 3G and 4G LTE services in Korea. In Korea, KT operates (i) LTE service on 900 MHz and 1.8 GHz, and (ii) 3G service on 2.1 GHz frequency bands. Our measurement software running on the smart phone records the available bandwidth of video streaming together with the GPS coordinates at every 1000 ms period. Figures 2(a) and 2(b) illustrate the our measurement architecture and equipments, respectively.

Our datasets first populate the location (skipped in Table 1), time, humidity, and speed, along with the 3G or 4G LTE networks. We have collected datasets at different times (6 am, noon, 6 pm, and midnight) on different days and with different humidity values (e.g., 30%-40% on a sunny day and 80%-90% on a rainy day). We also vary the speed of a mobile user from 4 km/h (walking speed) to 20 km/h (average vehicle speed on SNU campus) and 40 km/h (maximum vehicle speed on SNU campus). Throughout the 38 trips, which collectively took around 18 driving hours and 190 km, we have collected 12576 log data, each of which includes not only the above environmental/contextual information, but also the measured available bandwidth, cell ID number, location area code (LAC) number.

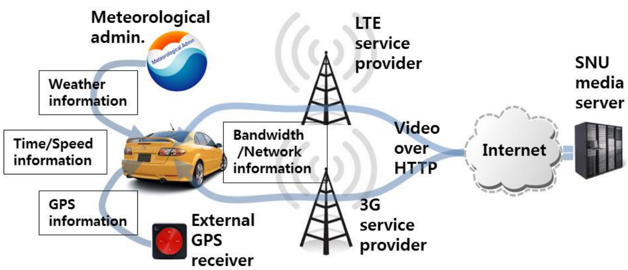
3. IMPACT ON AVAILABLE BANDWIDTH

3.1 Factor analysis

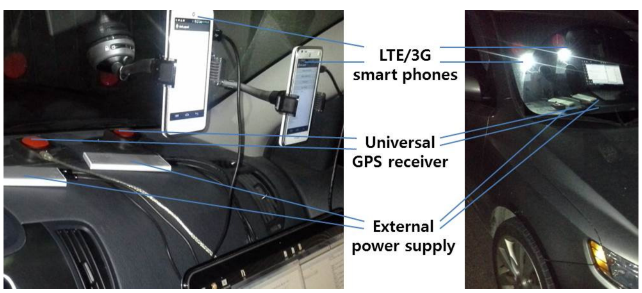
We investigate five environmental and context factors that affect the available bandwidth: (1) network type, (2) time, (3) humidity, (4) mobile speed, and (5) location. Note that, throughout this paper, the link bandwidth often indicates the throughput in the measurements. Table 1 shows the average throughput of each of 14 environmental/contextual settings. For the setting of pedestrian speed (5 km/h), we measured the throughput for 2 trips, while we have 3 measurement trips for the vehicular speed setting (20 and 40 km/h). Thus, there are 19 trips in each of the 3G and 4G LTE networks (total 38 trips).

Table 1: **Average throughput for each setting is summarized, where KBps is kilo bytes per second.**

Network Type	Time	Mobile speed	Relative humidity	Average throughput
3G	6 AM	40 Km/h	30%-40%	378.65 KBps
3G	Noon	40 Km/h	30%-40%	331.63 KBps
3G	6 PM	40 Km/h	30%-40%	304.20 KBps
3G	Midnight	40 Km/h	30%-40%	361.61 KBps
3G	Midnight	20 Km/h	30%-40%	372.02 KBps
3G	Midnight	5 Km/h	30%-40%	470.48 KBps
3G	Midnight	40 Km/h	80%-90%	249.86 KBps
4G LTE	6 AM	40 Km/h	30%-40%	1363.09 KBps
4G LTE	Noon	40 Km/h	30%-40%	853.30 KBps
4G LTE	6 PM	40 Km/h	30%-40%	828.76 KBps
4G LTE	Midnight	40 Km/h	30%-40%	1257.20 KBps
4G LTE	Midnight	20 Km/h	30%-40%	1363.09 KBps
4G LTE	Midnight	5 Km/h	30%-40%	1391.36 KBps
4G LTE	Midnight	40 Km/h	80%-90%	1278.58 KBps



(a) Measurement architecture



(b) Equipments

Figure 2: The measurement architecture and used equipments are shown, respectively. The equipments are installed in a car for the measurements with high speed.

3.1.1 Network Types: 3G vs. 4G LTE

In all settings, the 4G LTE network outperforms (3.52 times on average) 3G in terms of the throughput. The average throughput of the 4G LTE network is 1240.94 KBps while that of 3G is 352.64 KBps. This is merely because the 4G LTE network supports much higher bit rates leveraging technological enhancements like OFDMA and MIMO.

3.1.2 Time

To investigate the impact of time differences, we plot the measured throughput at two moments (i.e., 6 pm and midnight) in Figure 3. Note that x and y axes denote the latitude and longitude, respectively, and the thickness of each point indicates the measured throughput. Obviously, the average throughput at 6 pm (828.76 KBps) is significantly lower than the one at midnight (1608.42 KBps). Interestingly, 3G shows the relatively less throughput deviation at different times than 4G LTE. We conjecture this is partly because the number of 4G LTE users is greater than that of 3G users in [5].

The throughput degradation can be largely determined by the number of users since the cellular link bandwidth is shared among the users in the same cell. Since there are more users in 4G LTE, it is likely that the number of users in the 4G LTE network varies more severely, which results in the higher throughput variation than the 3G network.

3.1.3 Humidity

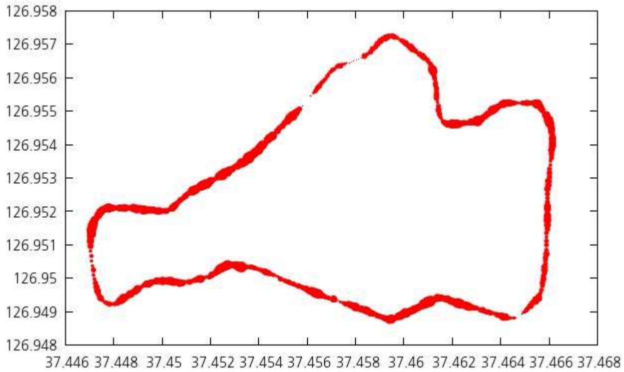
Another interesting observation is the effect of humidity on the available link bandwidth. To observe the correlation between the humidity and the link condition, we measure the throughput over the circular road (in Figure 1) on a rainy day. We find that 3G shows 31% throughput degradation while 4G LTE shows 21% degradation. This confirms the conventional wisdom that the rainy weather degrades the link condition. Interestingly, 3G exhibits more degradation than 4G LTE. We speculate that this phenomenon comes from the difference in frequency spectrum between 3G and 4G LTE. KT uses 900 MHz/1.8 GHz frequency bands for 4G LTE and 2.1 GHz for 3G. Since high frequency bands are more sensitive to humidity, 3G is expected to experience more signal attenuation.

3.1.4 Moving Speed

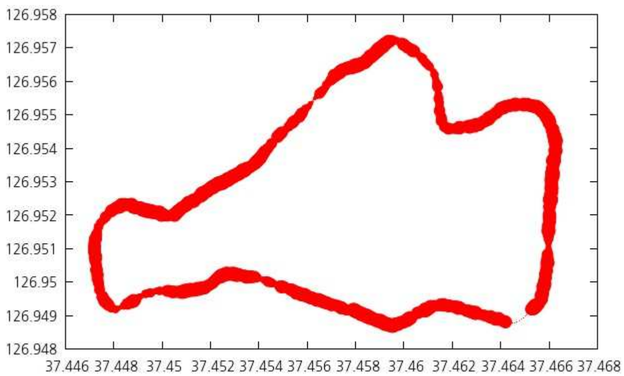
The moving speed of a user also turns out to affect the available link bandwidth. Both in 4G LTE and 3G networks, the average throughput is reduced as the moving speed is increased. Interestingly, severe bandwidth degradation appears at different places depending on the moving speed in 4G LTE network. By tracing cell ID changes, we conjecture that this is because much more frequent (approximately 30 times more) handovers take place in 4G LTE than in 3G.

3.1.5 Location

To investigate the correlation between the link bandwidth and the location, we plot throughput measurements over



(a) 6 PM



(b) Midnight

Figure 3: Throughput measurements along the circular road at (a) 6 pm and at (b) midnight in the 4G LTE network, where the thickness of each point indicates the throughput. The throughput at midnight is much higher than the one at 6 pm.

the circular road in Figure 4. In particular, we focus on the two locations A and B, which repeatedly show sudden throughput decrease in every measurement. As shown in Figure 4, the location is an important factor to predict the available link bandwidth.

3.2 Entropy analysis

To quantify the impact of the above factors on the available bandwidth of video streaming, we calculate the Shannon's entropy [14], a well-known metric which quantifies the level of uncertainty of a random variable. The entropy of a discrete random variable X is defined as,

$$H(X) = -\sum_{i}^{n} p(x) log_2 p(x).$$

where $p(x)$ is the probability mass function (PMF). For the mathematical tractability, we partition the continuous range of bandwidth (or throughput) values into a set of discrete subranges as shown in Table 2. By counting the number of throughput measurements which correspond to each subrange, we can compute the PMF for the 3G and 4G LTE networks, respectively, as plotted in Figure 5. If the PMF is uniformly distributed, its entropy can be calculated as $-log_2(1/n)$, where n is the number of subranges. In the case of 4G LTE, the entropy value is $-log_2(1/6) = 2.58$. With

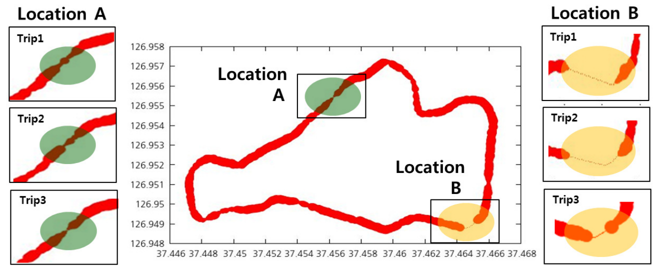


Figure 4: Throughput measurements along the circular road are shown in the 4G LTE network. Two representative locations A and B exhibit sudden throughput degradation repeatedly.

Table 2: The whole range of the measured throughput values is partitioned into the subranges for the 3G and 4G LTE networks as shown below.

3G	4G LTE
- 200 KBps	- 500KBps
200 KBps - 400 KBps	500 KBps - 1.0 MBps
400 KBps - 600 KBps	1.0 MBps - 1.5 MBps
600 KBps - 800 KBps	1.5 MBps - 2.0 MBps
800 KBps - 1.0 MBps	2.0 MBps - 2.5 MBps
1.0 MBps - 1.2 MBps	2.5 MBps -
1.2 MBps -	

the PMF in Figure 5, the entropy of the 4G LTE bandwidth over all measurements is calculated as 2.16, which is lower than that of the uniform distribution case.

We first investigate the location sensitivity of the throughput by calculating the *location entropy* $H(X|l_i)$, which is the entropy of the bandwidth for an individual location segment (of the circular road), l_i. $H(X|l_i)$ can be calculated as:

$$H(X|l_i) = -\sum_{i}^{n} p(x|l_i) log_2 p(x|l_i)$$

where $p(x|l_i)$ is the PMF of the throughput at location segment l_i. To calculate the location entropy, we divide our route (i.e., the circular road) into 20 location segments and generate the PMF of throughput values for each of the 20 segments. With the calculated PMFs, we compute the location entropy values for all the location segments. The average location entropy values are 1.50 and 1.79 in the 3G and 4G LTE networks, respectively, which are much lower than the entropy values without any information (i.e., 2.35 and 2.16 in 3G and 4G LTE, respectively). This indicates that the location information reduces the uncertainty of the bandwidth, and thus exploiting the location information can improve the accuracy of predicting the link bandwidth.

Similarly, we calculate the speed entropy $H(X|s_i)$, time entropy $H(X|t_i)$, and relative humidity (RH) entropy $H(X|rh_i)$ to quantify and compare the environmental and contextual factors. Table 3 summarizes the results of each entropy. As shown in Table 3, the location, time, and RH entropies are lower than the one without any information in 3G, which indicates that the location, time, and RH information can be exploited for better bandwidth prediction. Likewise, the

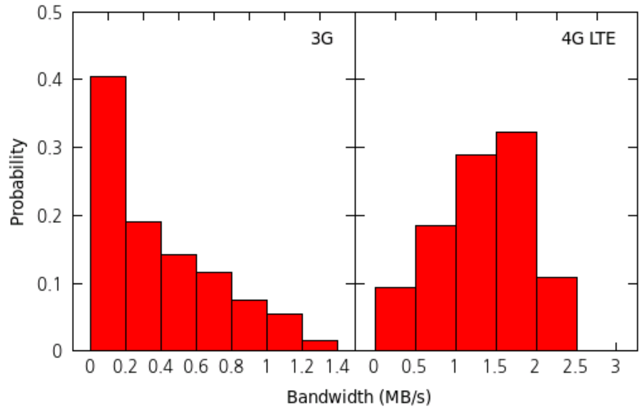


Figure 5: The PMFs of the throughput values for the 3G and 4G LTE networks are shown, respectively.

Table 3: Average entropy values depending on the location, moving speed, time, and relative humidity (RH) are shown. We also calculate the entropy values without any information and with uniform distribution, respectively.

	Loc.	Speed	Time	RH	No Info.	Uniform
3G	1.50	2.34	2.22	2.01	2.35	2.81
LTE	1.79	2.07	1.68	2.17	2.16	2.58

location, mobile speed, time entropy values are lower than the one without any information in 4G LTE, which signifies that these factors are important factors for bandwidth prediction.

Finally, we calculate the environmental entropy $H(X|e_i)$ which considers all of the above factors including the location, time, mobile speed, and humidity condition. The average entropy values are 1.21 and 1.03 for the 3G and 4G LTE networks, respectively. Since the location entropy are 1.5 and 1.79 for 3G and 4G LTE, respectively, this implies that if we consider the above factors when predicting the bandwidth, the uncertainty of the bandwidth is significantly reduced. In other words, the precision of predicting the bandwidth for better video streaming can be enhanced by considering the above factors.

4. MASERATI

In this section, we propose a mobile adaptive streaming scheme based on the environmental and contextual information (MASERATI). That is, MASERATI relies on the information of the location, time, humidity, and mobile speed to predict the available bandwidth. MASERATI consists of three parts: (1) MASERATI map build-up, (2) environmental and contextual information-based lookup, and (3) bandwidth estimation and video streaming scheduling.

Figure 6 illustrates the overall architecture of MASERATI. The MASERATI map database is constructed beforehand by wardriving. If a user requests a video segment (as in the DASH framework) with her/his current download throughput and environmental/contextual information (e.g., network type), MASERATI first finds the candidate bandwidth entries from the database that are matched by the user's current environments and contexts. Based on the current download throughput and the bandwidth information, MASERATI estimates the available bandwidth and decides the bit rate (or video quality) of the next video segment.

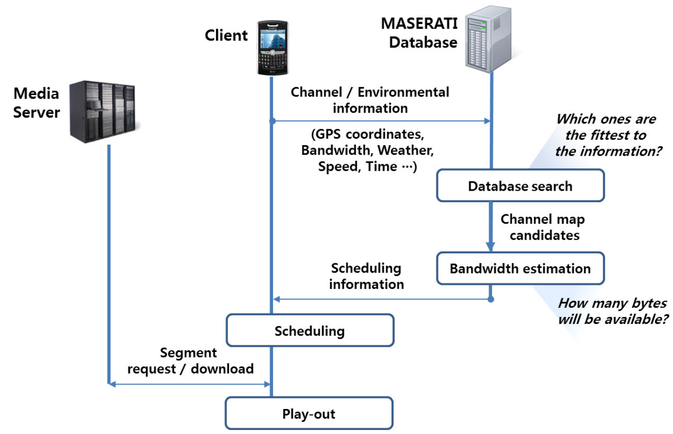


Figure 6: The architecture of MASERATI is illustrated.

4.1 MASERATI map build-up

To provide environmental/contextual information-aware video streaming services in MASERATI, the database is constructed beforehand. Each entry in the database consists of GPS coordinates, timestamp, download throughput, mobile speed, and network type (3G or 4G LTE). In addition, MASERATI retrieves the humidity information of the given location and time from the meteorological system. Updates of the MASERATI database can be performed either by the MASERATI service providers through wardriving or by MASERATI users through crowd-sourcing. That is, users can contribute to the improvement of the database by reporting their throughput and environmental/contextual information to MASERATI when they download a video.

4.2 Environmental/contextual information-based lookup

Upon receiving the request of a user with her/his environmental/contextual information, MASERATI finds the corresponding candidate entries from the database. MASERATI considers the different set of factors depending on the network types for bandwidth lookup. That is, the location and humidity information is exploited for 3G users while the location, time and mobile speed are mainly used for 4G LTE users. This is based on our observations in Section 3, which show that the available bandwidth of 3G is geo- and humidity-sensitive while that of 4G is geo-, time-, and speed-sensitive.

4.3 Bandwidth estimation and video streaming scheduling

To estimate the available bandwidth and decide the bit rate of the next video segment that will be downloaded, MASERATI considers both the current download throughput of a user and the expected bandwidth from the given environmental/contextual information from the database together. For the latter, we need to find the most similar database entry among multiple candidate entries that partially match with the current environmental/contextual setting of the user. For this, we calculate the Euclidean distance D between the environmental/contextual data of a given candidate entry C and the current setting of the mobile user M for a time window T at time t_0 as follows:

$$D(C, M) = \sqrt{\sum_{i=0}^{T-1} (B_M(t_0 - i) - B_C(t_0 - i))^2}$$

where $B_M(t)$ and $B_C(t)$ represent the throughput values of the mobile user and the candidate database entry at time t, respectively. Here, the unit of the time window is 1 second (denoted by i), and T can be a multiple of the duration of a video segment. By calculating the similarity, MASERATI can find the most suitable candidate entry that will be used for bandwidth prediction.

To minimize the gap between the current environment/context data of the mobile user and the recorded data of the selected candidate entry, MASERATI calculates a scale factor ρ, which is calculated as follows:

$$\rho = \frac{\sum_{i=0}^{T-1} B_M(t_0 - i)}{\sum_{i=0}^{T-1} B_C(t_0 - i)}$$

MASERATI then calculates the adjusted bandwidth from the selected database entry,

$$B_{MASERATI} = \frac{\rho}{W} \sum_{i=1}^{W} B_C(t_0 + i)$$

where W is the future time duration to predict the bandwidth (i.e., the duration of a video segment or its multiple).

Finally, MASERATI computes the available bandwidth B_A for the next video segment(s) at t_0 in a weighted average fashion as follows:

$$B_A = \alpha \cdot B_{MASERATI} + (1 - \alpha) \cdot B_M(t_0)$$

where α indicates the portion of reflecting the $B_{MASERATI}$ with respect to $B_M(t_0)$, the latest throughput of the user at t_0. While α can be a configurable parameter, we recommend to compute α by the cosine similarity between $B_M(\cdot)$ and $B_C(\cdot)$ for the latest interval T so that we aggressively reflect $B_{MASERATI}$ if the similarity is high.

5. EVALUATION

In this section, we evaluate how MASERATI enhances a user's QoE in mobile video streaming services in 3G and 4G LTE networks. To this end, we investigate four QoE metrics: (i) the playout rate is the ratio of the number of completely downloaded segments in the given deadlines to that of all the video segments, (ii) the quality of segments, (iii) the frequency of quality changes is the number of changes of video quality per time, and (iv) the degree of changed quality level is how many quality levels are upgraded or degraded per change. We compare MASERATI with (1) Pure-DASH which considers the current download throughput only, and (2) location-based DASH (LoDASH) which uses the location-based bandwidth prediction like [4, 12].

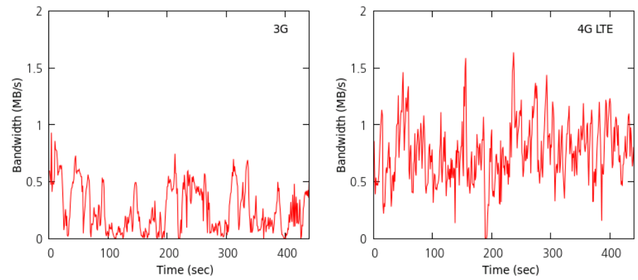


Figure 7: Throughput measurements (per second) of the test run over the circular road in the 3G and 4G LTE networks are plotted, respectively.

5.1 Test scenarios

We conduct experiments in two different scenarios: (i) video streaming in the 3G network at 12 am (midnight) on a rainy day with 80%-90% humidity, and (ii) video streaming in the 4G LTE network at 12 pm on a sunny day with 30%-40% humidity. Since the available bandwidth in the 3G network is substantially affected by the humidity as shown in Section 3, we collect an additional trace on a rainy day with high humidity for the first scenario. Similarly, we also collect another trace at the time when there are many active users for the second scenario since the time information is important for the available bandwidth in the 4G LTE network as shown in Section 3. Figure 7 shows the bandwidth fluctuation in the two scenarios.

We apply the three streaming algorithms to the above two scenarios: (i) Pure-DASH, (ii) LoDASH, and (iii) MASERATI. Each algorithm estimates the expected link bandwidth as follows. Pure-DASH estimates the link bandwidth based on the recently observed bandwidth during the latest interval (say, a multiple of the duration of a video segment). This algorithm assumes that the link quality measured during the latest time window will continue during the next interval. However, the link fluctuation may lead a noticeable disruption or degradation in video streaming services. LoDASH uses only the location part of the MASERATI map database to estimate the available bandwidth based on the user's current location. That is, LoDASH uses the average bandwidth of the given location from the MASERATI database to calculate the expected link bandwidth. Recall that we construct the MASERATI map database based on the collected datasets in Section 2. In addition, LoDASH also reflects the measured bandwidth (α = 40%) of the latest interval to balance the average link bandwidth of the given location and the latest link bandwidth (Refer to B_A). MASERATI estimates the expected available bandwidth as described in Section 4. For all the the three algorithms, we conservatively decide the final link bandwidth as 90% of the estimated one. Each algorithm then requests the maximum quality of the segment that the final bandwidth can accommodate. We set the duration of a video segment to 2 seconds, which is widely used in commercial adaptive streaming solutions like [17], and the quality levels (i) from 64 Kbytes at the lowest to 8564 Kbytes for the 3G network and (ii) from 464 Kbytes at the lowest to 8564 Kbytes for the 4G LTE network as recommended by [1] for mobile HTTP streaming.

Table 4: **Four QoE parameters of Pure-DASH, LoDASH, and MASERATI in the 3G and 4G LTE networks are shown, respectively. MASERATI outperforms Pure-DASH and LoDASH in most situations.**

QoE metrics	3G			LTE		
	Pure-DASH	LoDASH	MASERATI	Pure-DASH	LoDASH	MASERATI
Playout rate (%)	79.1	88.2	98.2	86.4	89.1	100
Average quality of segments	2.3	3.0	3.0	2.9	3.1	3.3
Quality change frequency (times/min)	22.2	9.1	11.7	24.8	11.5	17.0
Average quality change	1.7	1.3	1.3	1.9	1.5	1.2

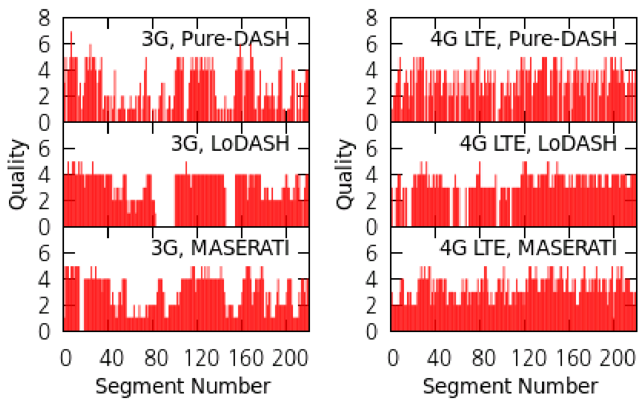


Figure 8: The quality variations of video streaming of the three algorithms in the 3G and the 4G LTE networks are plotted, respectively.

5.2 QoE in mobile video streaming

Figure 8 shows the quality variations of the received video segments in the two network settings. If downloading of a video segment fails (i.e., the segment is not downloaded until the beginning of its start time), its corresponding quality is measured as zero. As shown in Figure 8, the quality of the video segments exhibits a substantial fluctuation. The degree of fluctuation is severer in the case of Pure-DASH than the others, which reveals frequent playout failures. On the contrary, LoDASH and MASERATI show stable video quality since they additionally use the location information and the comprehensive environmental/contextual information, respectively.

Table 4 summarizes the QoE measurements in terms of the four metrics in each network setting: (i) the playout rate, (ii) the average quality of segments, (iii) the quality change frequency, and (iv) the average quality change. Overall, MASERATI outperforms Pure-DASH and LoDASH both in the 3G and the 4G networks. When we look at the playout rate, MASERATI exhibits almost perfect playout rates (98.2% and 100% in the 3G and 4G LTE networks, respectively). This demonstrates a substantial performance gain (24% and 16% for the 3G network and 4G LTE networks, respectively) compared to Pure-DASH. Also, the average quality of video segments in MASERATI is higher (30% and 14% for the 3G and 4G LTE networks, respectively) than that of Pure-DASH. Furthermore, MASERATI significantly improves the stability of video streaming than Pure-DASH in terms of the quality change frequency (47% and 31% for the 3G and 4G LTE networks, respectively) and the average quality change (24% and 37% for the 3G and 4G LTE networks, respectively). This indicates that MASERATI effectively enhances mobile video streaming services in terms of the four QoE metrics that affect the user experiences [7,18].

MASERATI and LoDASH show similar results in terms of the stability of video streaming because both of two algorithms reflect the average condition of the specific location. However, MASERATI outperforms (11% and 12% for the 3G and 4G LTE networks, respectively) LoDASH in terms of the playout rate since MASERATI further considers additional important factors for predicting the available bandwidth such as time, humidity, and moving speed. That is, LoDASH often fails to predict the available bandwidth accurately since it only uses the location information.

6. CONCLUSIONS

In this paper, we investigated the impact of various environmental/contextual information such as the location, time, humidity and mobile speed on the available bandwidth for stable mobile video streaming services. We found that the humidity, time, and location information are more important factors in the 3G network, while mobile speed, time, and location information are more crucial in the 4G LTE network for accurately predicting the available bandwidth. Based on the observations of what environmental/contextual information affects the available bandwidth, we proposed a new adaptive streaming system, MASERATI, where such information is comprehensively used to provide the video streaming services with the appropriate quality depending on the predicted link bandwidth. We demonstrated that MASERATI outperforms Pure-DASH and LoDASH in terms of the playout rate, video quality, and stability. Our ongoing work is to investigate whether a mobility model of a user can help predict the most appropriate quality of video streaming services.

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