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Robustic Video Streaming in Mobile Network Using SNS Based Prefetching

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Abstract

Due to the presence of many barriers for effective transmissions of videos in mobile networks we cannot cop up with the mobile user's requirements.

Nowadays,due to the traffic demand in the wireless communication,many problems such as poor service quality of video streaming over mobile network arise.To bare or decline such flaws,streaming technique is applied in cloud computing.On establishing various channel access links also,the gap between traffic demand and connection establishment can be bridged.The techniques such as TDMA which is based on time depending usage of the mobile users.Robustic video streaming enhances better streaming flow using scalable video coding. This technique has been advanced with SNS based prefetching in which prefetching decision can be taken based on relation between user and accessing histories recorded in client .This technique improves Qos.This SNS based prefetching enhables quick buffering and avoids packet losses and intermittent disruptions during transmission.The streaming supports wide spectrum of mobile devices.This keeps track of the social network interactions under the governance of an authorized private agent.Many techniques are applied here to obtain the predicted bandwidth and proper segment transfer.

I.Introduction

Although proceeding our life in 21st century,the drastic development period,we experience the problem of slow video transmissions like uploading,downloading,sharing,etc.. which is due to the low bandwidth capabilities.This technology solves such problems by following two properties.While receiving video streaming traffic via 3G/4G mobile networks, mobile users often suffer from long buffering time and intermittent disruptions due to the limited bandwidth and link condition fluctuation caused by multi-path fading and user mobility . Thus, it is crucial to improve the service quality of mobile video streaming while using the networking and computing resources efficiently .Recently there have been many studies on how to improve the service quality of mobile video streaming on two aspects:

• Scalability:

This measures the video coding performance.Also, the available link capacity of a mobile device may vary over time and space depending on its signal strength, other users traffic in the same cell, and link condition variation.Storing multiple versions (with different bit rates) of the same video content may incur high overhead in terms of storage and communication. To address this issue, the Scalable Video Coding (SVC) technique (Annex G extension)

of the H.264 AVC video compression standard defines a base layer (BL) with multiple enhance layers (ELs).These substreams can be encoded by exploiting three scalability features: (i) spatial scalability by layering image resolution (screen pixels), (ii) temporal scalability by layering the frame rate, and (iii) quality scalability by layering the image compression. By the SVC, a video can be decoded/played at the lowest quality if only the BL is delivered.However, the more ELs can be delivered, the better quality of the video stream is achieved.

•Robustiveness:

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Robustiveness ensures the receival of all the layers such as base layer(BL) and enhances other layers also.Traditional video streaming techniques designed by considering relatively stable traffic links

between servers and users, perform poorly in mobile environments . Thus the fluctuating wireless link status should be properly dealt with to provide 'tolerable‖ video streaming services. To address this issue, we have to adjust the video bit rate adapting to the currently time-varying available link bandwidth of each mobile user. Such adaptive streaming techniques can effectively reduce packet losses and bandwidth waste.Scalable video coding and adaptive streaming techniques canbe jointly combined to accomplish effectively the best possible quality of video streaming services. That is, we can dynamically adjust the number of SVC layers depending on the current link status .However most of the proposals seeking to jointly utilize the video scalability and adaptability rely on the active control on the server side. That is, every mobile user needs to individually report the transmission status (e.g., packet loss, delay and signal quality) periodically to the server, which predicts the available bandwidth for each user. Thus the problem is that the server should take over the substantial processing overhead, as the number of users increases.Cloud computing techniques are poised to flexibly provide

scalable resources to content/service providers, and process offloading to mobile users . Thus, cloud data centers can easily provision for large-scale real-time video services as investigated

in . Several studies on mobile cloud computing technologies have proposed to generate personalized intelligent agents for servicing mobile users, e.g., Cloudlet and Stratus. This is because, in the cloud, multiple agent instances (or threads) can be maintained dynamically and efficiently depending on the time-varying user demands.Recently social network services (SNSs) have been increasinglypopular. There have been proposals to improve the quality of content delivery using SNSs . In SNSs, users may share, comment or re-post videos among friends and members in the same group, which implies a user may watch a video that her friends have recommended

.Usersin SNSs can also follow famous and popular users based on their interests (e.g., an official facebook or twitter account that shares the newest pop music videos), which is likely to be watched by its followers.In this regard, we are furthermotivated to exploit the relationship among mobile users from their SNS activities in order to prefetch in advance the beginning part of the video or even the whole video to the members of a group who have not seen the video yet. It can be done by a background job supported by the agent (of a member) in the cloud; once the user clicks to watch the video, it can instantly start playing.In this paper, we design a adaptive video streaming and prefetching framework for mobile users with the above objectives in mind, dubbed this method.Cloud constructs a private agent for each mobile user in cloud computing environments,which is used by its two main parts: (i) RMoV(robusticmobile video streaming), and (ii)ESoV(efficient social videosharing). The contributions of this paper can be summarized as follows:

• RMoV offers the best possible streaming experiences by adaptively controlling the streaming bit rate depending on the fluctuation of the link quality.RMoVadjusts the bit ratefor each user leveraging the scalable video coding. The private agent of a user keeps track of the feedback information on the link status. Private agents of users are dynamically initiated and optimized in the cloud computing platform.

Also the real-time SVC coding is done on the cloud computing side efficiently.

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• This Cloud supports distributing video streams efficiently by facilitating a 2-tier structure: the first tier is a content delivery network, and the second tier is a data center.With this structure, video sharing can be optimized within the cloud. Unnecessary redundant downloads ofpopular videos can be prevented .

• Based on the analysis of the SNS activities ofmobileusers,ESoV seeks to provide a user with instant playing of video clips by prefetching the video clips in advance from her private agent to the local storage of her device. The strength of the social links between users and the history of varioussocial activities can probabilistically determine how much and which video will be prefetched.The rest of the paper is organized as follows. We first introduce related work in Section II, and explain the Cloud framework in Section III. The adaptive video streaming serviceand the efficient social video sharing will be detailed in Sections IV and V, respectively. Then the operations of this Cloudis illustrated in Section VI. Finally, we evaluate the prototype implementation in Section VII, and conclude the paper in Section VIII.

II. RELATED WORK

A.Robustic Video Streaming Techniques

In the adaptive streaming, the video traffic rate is adjusted on the fly so that a user can experience the maximum possible video quality based on his or her link's time-varying bandwidth capacity. There are mainly two types of adaptive streaming techniques, depending on whether the adaptivity is controlled by the client or the server. The Microsoft's Smooth

Streaming is a live adaptive streaming service which can switch among differentbit rate segmentsencodedwithconfigurablebit rates and video resolutions at servers, while clients dynamically requestvideos based on local monitoring of link quality. Adobe andApple also developed client-side HTTP adaptive live streamingsolutions operating in the similar manner. There are also somesimilar adaptive streaming services where servers controls theadaptive transmission of video segments, for example, theQuavliveAdaptive Streaming. However,most of these solutionsmaintain multiple copies of the video content with differentbit rates, which brings huge burden of storage on the server.Regarding rate adaptation controlling techniques, TCPfriendlyrate control methods for streaming services over mobile networks are proposed , where TCP throughputof a flow is predicted as a function of packet loss rate, round triptime, and packet size. Considering the estimated throughput,the bit rate of the streaming traffic can be adjusted. A rateadaptation algorithm for conversational 3G video streaming is introduced by . Then, a few

cross-layer adaptationtechniques are discussed , which can acquire moreaccurate information of link quality so that the rate adaptationcan be more accurately made. However, the servers have toalways control and thus suffer from large workload.Recently the H.264 Scalable Video Coding (SVC) technique has gained a momentum . An adaptive video streamingsystem based on SVC is deployed in , which studies thereal-time SVC decoding and encoding at PC servers. The work

in proposes a quality-oriented scalable video delivery

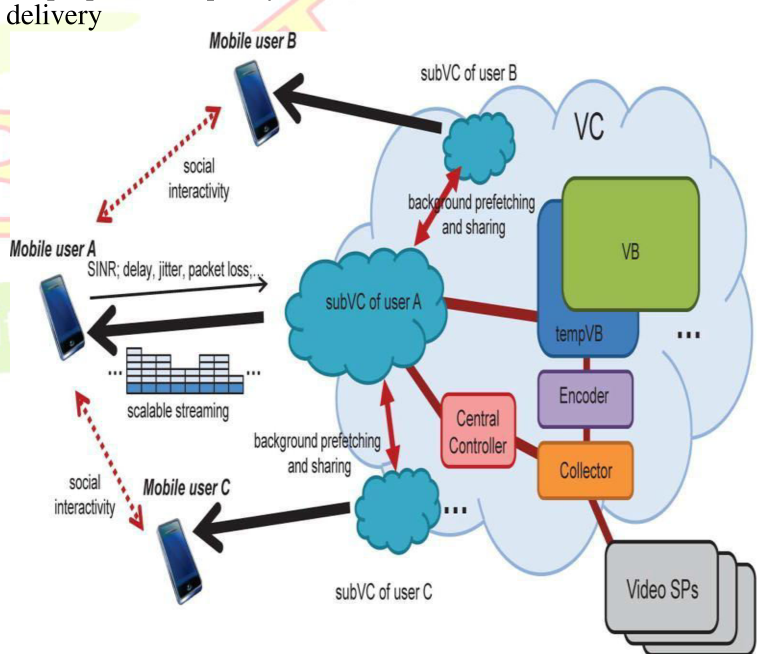

Fig. 1. Illustration of the AMES-Cloud framework with the Video Cloud (VC), subVCs

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for mobile users, the Video Base (VB), and the Video Service Providers(SPs).

using SVC, but it is only tested in a simulated LTE Network.Regarding the encoding performance of SVC, CloudStreammainly proposes to deliver high-quality streaming videosthrough a cloud-based SVC proxy , which discovered thatthe cloud computing can significantly improve the performance

of SVC coding. The above studies motivate us to use SVC forvideo streaming on top of cloud computing.

B. Mobile Cloud Computing Techniques

The cloud computing has been well positioned to providevideo streaming services, especially in the wired Internetbecause of its scalability and capability. For example,the quality-assured

bandwidth auto scaling for VoDstreamingbased on the cloud computing is proposed, and the CALMSframework is a cloud-assisted live media streaming servicefor globally distributed users. However, extending the cloud computing-based services to mobile environments requiresmore factors to consider: wireless link dynamics, user mobility,the limited capability of mobile devices. More recently,new designs for users on top of mobile cloud computingenvironments are proposed, which virtualize private agentsthat are in charge of satisfyinh the requirements (e.g., QoS) ofindividual users such as Cloudlets and Stratus.Thus,

we are motivated to design the Cloud framework byusing virtual a gents in the cloud to provide adaptive videostreaming services.

III. CLOUD FRAMEWORK

In this section we explain the AMES-Cloud framework includesthe Adaptive Mobile Video streaming (AMoV) and theEfficient Social Video sharing (ESoV).As shown in Fig. 1, the whole video storing and streamingsystem in the cloud is called the Video Cloud (VC). In the VC,there is a large-scale video base (VB), which stores the most ofthe popular video clips for the video service providers (VSPs).Atemporal video base (tempVB) is used to cache new candidatesfor the popular videos, while tempVB counts the access frequencyof each video. The VC keeps running a collector to seekvideos which are already popular in VSPs, and will re-encodethe collected videos into SVC format and store into tempVBfirst. By this 2-tier storage, the AMES-Cloud can keep servingmost of popular videos eternally. Note that management workwill be handled by the controller in the VC.Specialized for each mobile user, a sub-video cloud (subVC)is created dynamically if there is any video streaming demandfrom the user. The sub-VC has a sub video base (subVB), whichstores the recently fetched video segments. Note that the videodeliveries among the subVCs

and the VC in most cases are actuallynot ―copy‖, but just ―link‖ operations on the same fileeternally within the cloud data center. There is also encodingfunction in subVC (actually a smaller-scale encoder instanceof the encoder in VC), and if the mobile user demands

a new video, which is not in the subVB or the VB in VC, thesubVC will fetch, encode and transfer the video. During videostreaming, mobile users will always report link conditions totheir corresponding subVCs, and then the subVCs offer adaptivevideo streams. Note that each mobile device also has a temporarycaching storage, which is called local video base (localVB),and is used for buffering and prefetching.Note that as the cloud service may across different places,or even continents, so in the case of a video delivery andprefetching between different data centers, an transmission willbe carried out, which can be then called ―copy‖. And because ofthe optimal deployment of data centers, as well as the capable

links among the data centers, the ―copy‖ of a large video file takes tiny delay.

IV. AMOV: ADAPTIVE MOBILE VIDEO STREAMING

A. SVC

As shown in Fig. 2, traditional video streams with fixed bitrates cannot adapt to the fluctuation of the link quality. For a particularbit rate, if the sustainable link bandwidth

variesmuch, thevideo streaming can be frequently terminated due to the packetloss.In SVC, a combination of the three lowest scalability iscalled the Base Layer (BL) while the enhanced combinationsare called

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Enhancement Layers (ELs). To this regard, if BL

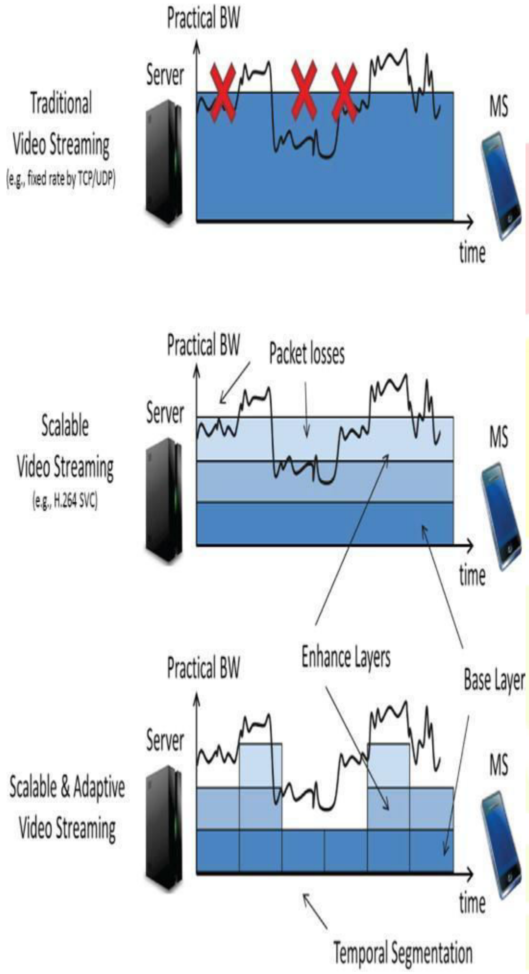

Fig. 2. A comparison of the traditional video streaming, the scalable video streaming and the streaming in the AMES-Cloud framework.

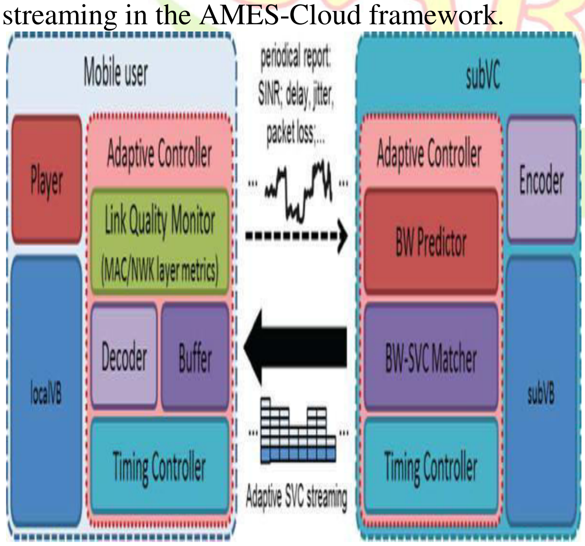

Fig. 3. Functional structure of the client and the subVC.

is guaranteed to be delivered, while more ELs can be alsoobtained when the link can afford, a better video quality canbeexpected.By using SVC encoding techniques, the server doesn't needto concern the client side or the link quality. Even some packetsare lost, the client still can decode the video and display. Butthis is still not bandwidth-efficient due to the unnecessary packetloss. So it is necessary to control the SVC-based video streamingat the server side with the rate adaptation method to efficiently utilize the bandwidth.

B. Adaptability With Monitoring on Link Quality

We design the mobile client and the subVC with the structureas shown in Fig. 3. The link quality monitor at mobile clientkeeps tracking on metrics including signal strength, packetround-trip-time (RTT), jitter and packet loss with a certain dutycycle. And the client will periodically report to the subVC.

Hereby we define the cycle period for the reporting as the ―timewindow‖, denoted by ,

Note that the video is also split bytemporal segmentation by interval .Once the subVC gets the information of the link quality, it willperform a calculation and predict the potential bandwidth in thenext time window.

Note that we will use ―predicted bandwidth‖and ―predicted goodput‖ interchangeably in following parts.

Suppose sequence number of current time window is ,thepredicted bandwidth can be estimated by:

where, indicating the importance of each factor,is for packet loss rate, is for RTT, is for thesignal to interference and noise ratio, and , , are threefunctions reflecting the value change of each factor compared

with that of last time window.Actually in this paper we deploy a measurement-based prediction,

that is we directly use of last time windowas the of next time window, which is proved with already high accuracy.

C. Matching Between Bandwidth Prediction and SVCSegments

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After obtaining the predicted bandwidth, or say goodput, ofnext time window, subVC will match and decide how manyvideo segments of BL and ELs can be transmitted approximately.We hereby define the term ―resolution‖ to indicate thelevel of temporal segmentation and the number of ELs. Ifis small and there are more ELs, we say the SVC-based videosource is with a higher resolution. We illustrate two cases of

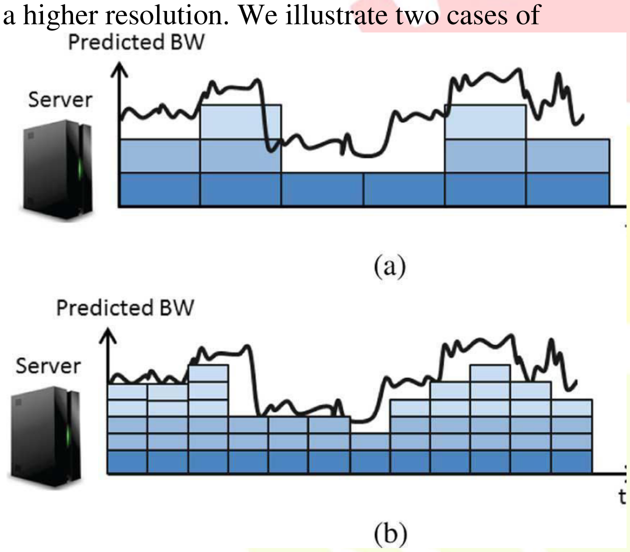

Fig. 4. Matching between predicted bandwidth and SVC-segments with different resolutions. (a) Fine-grained (high resolution). (b) Coarse-grained (lowresolution).

coarse-grained (low resolution) and a relatively fine-grained(high resolution) for matching between the SVC segmentsand the predicted goodput in Fig. 4. The resolution with twoELs and a larger can hardly fit to the signal fluctuation,and thus there are some bandwidth wasted or packets lost. In contrast a higher

resolution with more ELs and a smallercan always fit the fluctuation of the bandwidth. However ahigher resolution also induces more encoding workload to theservers.Suppose there are totally ELs, and the bit rate of the thEL is denoted as while the bit rate of the BL is).We let indicate the SVC segment of BL with temporal sequence, and let indicate the SVC segment of the thELwith temporal sequence . So the algorithm ofmatchingbetweenpredicted bandwidth and SVC segments is shown in Algorithm1 as following:

Algorithm 1Matching Algorithm between BW and Segments

i=0
$BW_o=R_{BL}$
TransmitBL_o
Monitor$BW_o^{practical}$
repeat
Sleep for T_{win}
Obtain ,p_i ,RTT_i,$SINR_i$ etc., from client's report
Predict $BW_{i+1}^{estimate}$ (or $BW_{i+1}^{estimate}=BW_i^{practical}$)
k=0
$BW_{EL}=0$
repeat
k++
if k>=j break
$BW_{EL}=BW_{EL}+ R_{EL}^{k}$
until$BW_{EL}>=BW_{i+1}^{estimate} - R_{BL_2}$
Transmit BL_{i+1} and EL_{i+1}^{1},EL_{i+1}^{2},…,EL_{i+1}^{k-1}
Monitor $BW_{i+1}^{practical}$
i++
untilAll video segments are transmitted

V. ESOV: EFFICIENT SOCIAL VIDEO SHARING

A. Social Content Sharing

In SNSs, users subscribe to known friends, famous people,and particular interested content publishers as well; also thereare various types of social activities among users in SNSs, suchas direct message and public posting. For spreading videos inSNSs, one can post a video in the public, and his/her subscribers

can quickly see it; one can also directly recommend a video tospecified friend(s); furthermore one can periodically get noticedby subscribed content publisher for new or popular

videos.Similar to studies in, we define different strengthlevels for those social activities to indicate the probability thatthe video shared by one user may be watched by the receiversof the one's sharing activities, which is called a

―hitting probability‖,so that subVCs can carry out effective backgroundprefetching at subVB and even localVB. Because after a videosharing activity, there may be a certain delay that the recipientgets to know the sharing, and initiates to watch.Thereforethe prefetching in prior will not impact the users at most cases.Instead, a user

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can click to see without any buffering delay asthe beginning part or even the whole video is already prefetchedat the localVB. The amount of prefetched segments is mainly

determined by the strength of the social activities. And theprefetching from VC to subVC only refers to the ―linking‖action, so there is only file locating and linking operationswith tiny delays; the prefetching from subVC to localVBalsodepends on the strength of the social activities, but will alsoconsider the wireless link status.We classify the social activities in current popular SNSs intothree kinds, regarding the impact of the activities and the potentialreacting priority from the point of view of the recipient:

VI.Influence of SNS in the domain of mobile users:

People use social networking sites for meeting new friends, finding old friends, or locating people who have the same problems or interests they have, called niche networking.More and more relationships and friendships are being formed online and then carried to an offline setting. Psychologist and University of Hamburg professor Erich H. Witte says that relationships which start online are much more likely to succeed. Witte has said that in less than 10 years, online dating will be the predominant way for people to start a relationship. One online dating site claims that 2% of all marriages begin at its site, the equivalent of 236 marriages a day. Other sites claim one in five relationships begin online.Users do not necessarily share with others the content which is of most interest to them, but rather that which projects a good impression of themselves. While everyone agrees that social networking has had a significant impact on social interaction, there remains a substantial disagreement as to whether the nature of this impact is completely positive. A number of scholars have done research on the negative effects of internet communication as well. These researchers have contended that this form of communication is an impoverished version of conventional face-to-face social interactions, and therefore produce negative outcomes such as loneliness and depression for users who rely on social networking entirely. By engaging solely in online communication, interactions between communities, families, and other social groups are weakened.

B. Prefetching Levels

Different strengths of the social activities indicate differentlevels of probability that a video will be soon watched by the recipient.Correspondingly we also define three prefetching levels
regarding the social activities of mobile users:

• ―Parts‖: Because the videos that published by subscriptionsmay be watched by the subscribers with a not highprobability, we propose to only push a part of BL and ELssegments, for example, the first 10% segments.

• ―All‖: The video shared by the direct recommendationswill be watched with a high probability, so we propose toprefetch the BL and all ELs, in order to let the recipient(s)directly watch the video with a good quality, without anybuffering.

• ―Little‖:Thepublic sharinghas a weak connectivityamong users, so the probability that a user's friends

(followers) watch the video that the user has watched orshared is low.We propose to only prefetch the BL segmentof the first time window in the beginning to those whohave seen his/her activity in the stream.The prefetching happens among subVBs and the VB, alsomoreimportantly,will be performed from the subVB to localVBof the mobile device depending on the link quality. If a mobileuser is covered by Wi-Fi access, due to Wi-Fi's capable linkand low price (or mostly for free), subVC can push as muchas possible in most cases. However if it is with a 3G/4Gconnection, which charges a lot and suffers limited bandwidth,we propose to downgrade the prefetching level to save energyand cost as listed in Table I, but users can still benefit fromthe prefetching effectively. Note that some energy prediction methods can be deployed in order to actively decide whethercurrent battery status is suitable for ―parts‖ or ―little‖.If a user, A, gets the direct recommendation of a video fromanother user, B,

A's subVC will immediately prefetchthevideo either from B's subVB, or from the VB (or tempVB)at the level of ―all‖, if A is with Wi-Fi access. Howeverif user A is connected to 3G/4G link, we will selectivelyprefetch a part of the

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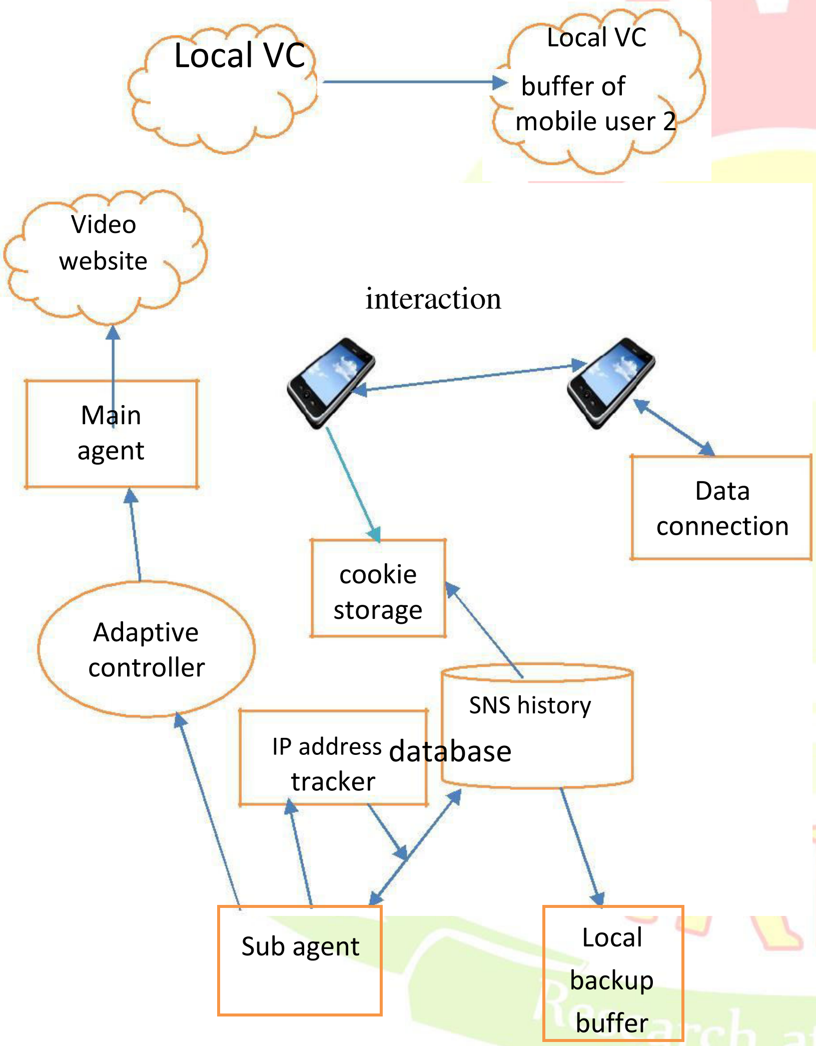
video segment to A's local storage atthe level of ―parts‖. Note that the subscribed videos will benotprefetched when user A is at 3G/4G connection, as itis downgraded from ―little‖ to none.A better extension of the prefetching strategy by social activitiescan be designed by PREFETCH MECHANISM:



VII.Issues

A.Privacy

Privacy concerns with social networking services have been raised growing concerns amongst users on the dangers of giving out too much personal information and the threat ofsexual predators. Users of these services also need to be aware of data theft or viruses. However, large services, such as MySpace and Netlog, often work with law enforcement to try to prevent such incidentsIn addition, there is a perceived privacy threat in

an self-updating mechanism from theuser's hitting history in an evolutionary manner. This learning based prefetching is out of the scope of this paper, and will be explored as our future work.

relation to placing too much personal information in the hands of large corporations or governmental bodies, allowing a profile to be produced on an individual's behavior on which decisions, detrimental to an individual, may be taken.Furthermore, there is an issue over the control of data—information that was altered or removed by

the user may in fact be retained and passed to third parties. This danger was highlighted when the controversial social networking site Quechup harvested e-mail addresses from users' e-mail accounts for use in a spamming operation.In medical and scientific research, asking subjects for information about their behaviors is normally strictly scrutinized by institutional review boards, for example, to ensure that adolescents and their parents have informed consent. It is not clear whether the same rules apply to researchers who collect data from social networking sites. These sites often contain a great deal of data that is hard to obtain via traditional means. Even though the data are public, republishing it in a research paper might be

considered invasion of privacy.Privacy on social networking sites can be undermined by many factors. For example, users may disclose personal information, sites may not take adequate steps to protect user privacy, and third parties frequently use information posted on social networks for a variety of purposes. "For the Net generation, social networking sites have become the preferred forum for social interactions, from posturing and role

playing to simply sounding off. However, because such forums are relatively easy to access, posted content can be reviewed by anyone with an interest in the users' personal information".Following plans by the UK government to monitor traffic on social networksschemes similar to e-mail jamming have been proposed for networks such as Twitter and Facebook. These would involve "friending" and "following" large numbers of random people to thwart attempts at network analysis.Privacy concerns have been found to differ between users according to gender and personality. Women are less likely to publish information that reveals methods of contacting them. Personality measures openness, extraversion, and conscientiousness were found to positively affect the willingness to disclose data, while neuroticism decreases the willingness to disclose personal information.

VIII. VIDEO STORAGE AND STREAMING FLOWBY AMOV AND EMOS

The two parts, AMoV and EMoS, in AMES-Cloud frameworkhave tight connections and will together service the videostreaming and sharing: they both rely on the cloud computingplatform and are carried out by the private agencies of users;while prefetching in EMoS, the AMoV will still monitor andimprove the transmission considering the link status; with a certainamountof prefetched segments by EMoS, AMoV can offerbetter video quality.With the efforts of AMoV and EMoS, we illustrate the flowchart of how a video will be streamed in Fig. 5.Note that in orderto exchange the videos among the localVBs, subVBs, tempVBand the VB, a video map (VMap) is used to indicate the requiredsegments.Once a mobile user starts to watch a video by a link, the localVBwill first be checked whether there is any prefetched segments of the video so that it can directly start. If there is none or just some parts, the client will report a corresponding V Map to its subVC. if the subVC has prefetched parts in subVB, the subVC will initiate the segment transmission. But if there isalso none in the subVB, the tempVB and VB in the center VCwill be checked. For a non-existing video in AMES-Cloud, thecollector in VC will immediately fetch it from external videoproviders via the link; after re-encoding the video into SVCformat, taking a bit longer delay, the subVC will transfer to themobileuser.Also in AMES-Cloud, if a video is shared among the subVCsat a certain frequency threshold (e.g., 10 times per day), it willbe uploaded to the tempVB of the VC; and if it is further sharedat a much higher frequency (e.g., 100 times per day), it will bestored with a longer lifetime in the VB. In such a manner, whichis quite similar to the leveled CPU cache, the subVB and VBcan always store fresh and popular videos in order to increasethe probability of re-usage.

IX. IMPLEMENTATION AND EVALUATION

We evaluate the performance of the AMES-Cloud frameworkby a prototype implementation. We choose the U-cloud server(premium) in the cloud computing service offered by KoreanTelecom, and utilize the virtual server with 6 virtual CPU cores(2.66 GHz) and 32 GB memory, which is fast enough for encoding 480P (480 by 720) video with H.264 SVC format in30 fps at real time [9]. In the cloud, we deploy our server applicationbased on Java, including one main program handling alltasks of the whole VC, while the program dynamically initializes,maintains and terminates instances of another small Javaapplication as private agents for all active users. We implementthe mobile client at a mobile phone, Samsung Galaxy II, withandroid system version 4.0. The mobile data service is offeredby LG LTE network, while in some uncovered area the 3Gnetwork is used.

Note that we still use ―3G‖ to indicate the generalcellularnetwork.We test in the downtown area, so the practicalbandwidth of the mobile link is not as high as we expected,but this won't impact our experiment results.The test video is the Tomb Raider 2012 Trailer in H.264format with 480P resolution downloaded from YouTube. Its size

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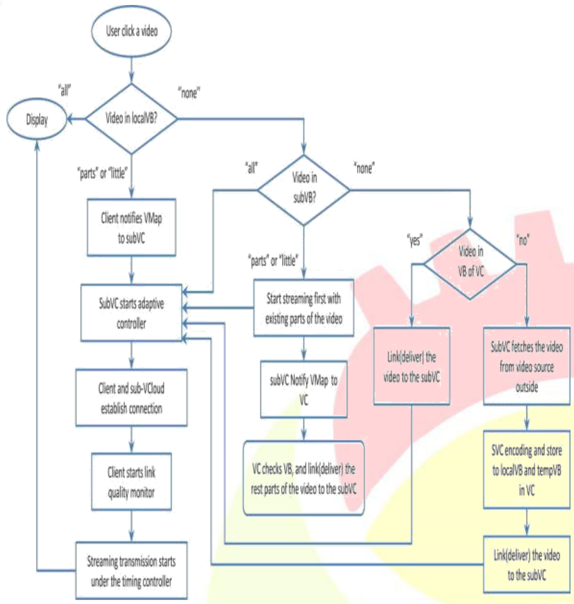

Fig. 5. Working flow of video streaming in the subVC and VC of AMES-Cloud framework.

is 13.849 Mbytes and with a duration of 180 seconds. We firstdecode it by the x264 decoder into the YUV format, and re-encodeit by the H.264 SVC encoder, the Joint Scalable VideoModel (JSVM) software of version 9.1. We just use defaultsettings for the decoding and encoding, and do the H.264

SVC encoding at the virtual server in the cloud. We split the video into segments by 1 second to 5 seconds,that is to vary$T_{win}$with values 1s, 2s, 3s, 4s and 5s. By JSVM,besides the base layer, we further make five temporal layers(1.875, 3.75, 7.5, 15, and 15 fps), two spatial layers (240 by360 and 120 by180) and two more quality layer (low and high),referring to [12] and [40]. Thus we define the best resolution

configuration as ―1+5+2+2‖. And we also test different resolutionconfigurations, including

―1+1+1+1‖, ―1+2+2+2‖, ―1+3+2+2‖ and ―1+4+2+2‖.

A. Adaptive Video Streaming Based on SVC

Firstly we examine whether there is a deep relationshipbetween the measured bandwidth of last time window andthe practical bandwidth of next time window (goodput by Kbps). We test the video streaming service via cellular link,and move the device around in the building to try to changethe signal quality. Note that all tests are ran five times. Thecollected the relative errors for the predicted bandwidth tothe practical bandwidth for every time window, calculatedby |$BW^{estimate}$ - $BW^{practical}$|/{$BW_{practical}$},are shownin Fig. 6, where the bar indicates the 25% and 75% quartiles,and the whiskers indicate the 5% and 95% percentiles. When$T_{win}$is 1 second or 2 seconds, the predicted bandwidth is verynear to the practical one with around 10% relative error, butlarge values ofT_{win}have relatively poor prediction accuracy,

which reflects the similar results. So we suggest a short$T_{win}$of 2 or 3 seconds for accurate prediction in practicaldesigns

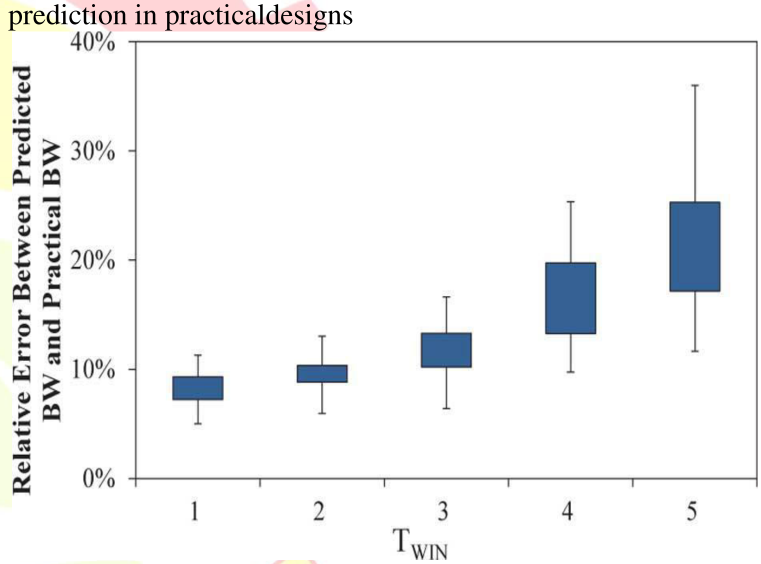

Fig. 6. Relative errors between predicted bandwidth and practical bandwidth(percentage).

B. Video Streaming in SubVC and VC

We evaluate how H.264 SVC works in AMES-Cloud frameworkregarding the above mentioned SVC resolution configurations.As shown in Fig. 7(a), because of the strong computationalcapacity by the cloud computing, the encoding speed isfast. The best resolution configuration ―1+5+2+2‖with 5

second temporal segmentation scheme requires about 560 msfor encoding. For shorter intervals of T_{win}, the encoding delayis very small under 50 ms.Because more ELs induce higher overhead due to the duplicatedI-frames, we test the overhead, which is calculated by theratio of the total size of the video segments after SVC encodingto the size of only the BL. As shown in Fig. 7(b), the resolutionscheme of

―1+1+1+1‖ has a low overhead around below10%, and ―1+2+2+2‖ with two ELs for

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each scalabilityfeature has about 17% overhead, which is acceptable. Howeverhigher resolution like ―1+4+2+2‖ has 61% overhead, and ―1+5+2+2‖ has even 120% overhead, which is not efficient.Overall, an SVC stream should not contain too many enhancelayers for extremely high scalability, which may practicallybring too much overhead.

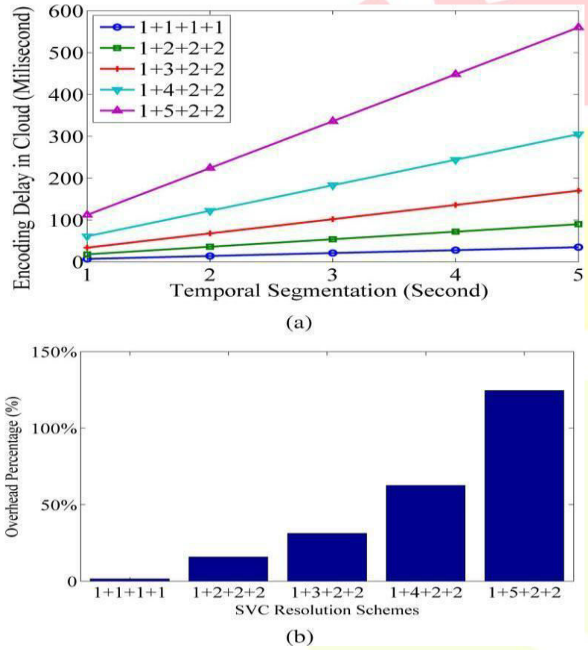

Fig. 7. Evaluation of SVC resolution schemes.

(a) Delay of difference SVCresolution schemes in the Cloud (b) Overhead of different SVC resolutionsschemes in the Cloud.

TABLE II

DELAYS OF PREFETCHING SHARING FOR VARIOUS LEVELS

	Little	Parts
subVBs↔VB	0.011 s	0.023 s
subVB→locVB via Wi-Fi	2.421 s	4.359 s
subVB→locVB via 3G	N&A	18.430 s (little)

C. Prefetching Delays

In ESoV, video segments can be prefetched among VB,tempVB, and localVBs of the mobile users, based on theiractivities in SNSs. we evaluate the required delays for differentlevels of prefetching as shown in Table. 2. We here use thenormal resolution configuration of ―1+2+2+2‖ with 2second temporal segmentation by default (the same in followingtests). We also set the sharing length of ―little‖ as only the first 5 seconds of the BL and ELs, that of ―parts‖ as the first15 seconds of the BL and ELs, and that of ―all‖ as all BL andELssegments.We can see that prefetching supported by the cloud computing is significantly fast.When prefetching via wireless links, it takesseveral seconds. However it is obvious that in most cases,a recipient of the video sharing may not watch immediatelyafter the original sharing behavior, that is normal users havesignificant access delay gaps, so this prefetching transmission delay won't impact user's experience at all, but will bring ―non-buffering‖ experience in fact when the user clicks to watch at a later time.

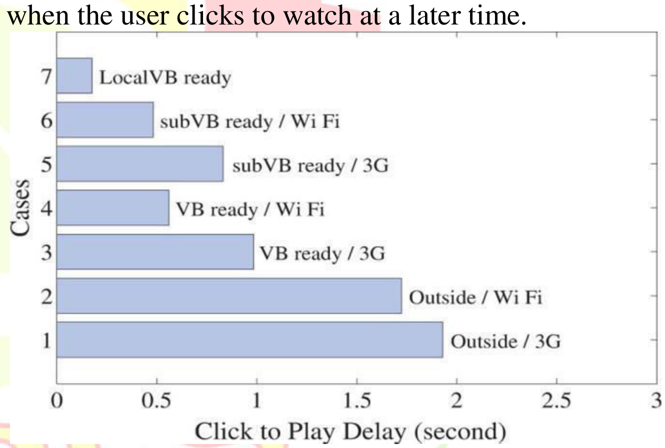

Fig. 8. Average click-to-play delay for various cases.

D. Watching Delay

We test how long one user has to wait from the moment thatone clicks the video in the mobile device to the moment thatthe first streaming segment arrives, which is called as ―click-toplay‖delay. As shown in Fig. 8, if the video has been cachedinlocalVB, the video can be displayed nearly immediately withignorable delay. When we watch video which is fetched fromthesubVC or the VC, it generally takes no more than 1 secondto start. However if the user accesses to AMES-Cloud servicevia the cellular link, he will still suffer a bit longer delay (around1s) due to the larger RTT of transmission via the cellular link.

For the cases to fetch videos which are not in the AMESCloud(but in our server at lab), the delay

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is a bit higher. Thisis mainly due to the fetching delay via the link from our serverat lab to the cloud data center, as well as the encoding delay. Inpractical, there are be optimized links in the Internet backboneamongvideo providers and cloud providers, and even recentvideo providers are just using cloud storage and computing service.Therefore this delay can be significantly reduced in practice.Also this won't happen frequently, since most of the popularvideos will be already prepared in the AMES-Cloud.

Conclusion

In this paper,we discussed our proposal of an robustic mobile video streaming and social network interactions, which is our advanced robustic video streaming efficiently stores videos in the clouds (VC), and utilizes cloud computing to construct private agent (subVC) for each mobile user to try to offer ―ALBV‖(Anytime Low-Buffered Video).With this technique the user's communication in the virtual world is identified and predicted to fulflll their downloading or online procedures with the storage buffers.Privacy concerns with social networking services have been raised growing concerns amongst users on the dangers of giving out too much personal information and the threat ofsexual predators. Users of these services also need to be aware of data theft or viruses. However, large services, such as MySpace and Netlog, often work with law enforcement to try to prevent such incidents .We evaluated the prefetching by prototype implementation and shows that the cloud computing technique with the involvement of SNS brings significant improvement on the robustiveness of the mobile streaming.The objective is to verify how cloud computing can improve the video transmission and low latency for mobile users. In the future,we will also try to improve the security issues in the Cloud.

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