A Novel Incentive Consistent Peer Selection Mechanism

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Abstract

The typical methods proposed to improve the Qos (Quality of Service) of streaming are discussed on two aspects: peer selection and data assignment. Since most of the recent peer selection mechanisms used in streaming system hasn’t taken peer’s historical behavior into account, this paper introducs a novel incentive consistent peer selection mechanism and a novel peer selection algorithm based on bidding model in game theory. And the experimental results show that the novel incentive consistent peer selection algorithm is better than other algorithm used in P2P media streaming service.

Keywords: P2P, Incentive consistent, Game theory, Qos.

1. Introduction

P2P application has played an important rule on Internet application during recent years. According to an authoritative statistic, since 2004, the amount use of video stream has exceeded audio stream which means the traditional P2P file sharing network is to be used mostly for TV and film transportation. As a typical P2P application, VOD (Video on Demand) is likely to be concerned with public. In a P2P VOD system, user attaches most importance to streaming Qos. Studies on how to improve media stream Qos emphasis on two aspects: peer selection and data assignment. Previous researches have worked a lot on data assignment; the two main methods used here are package-level based [1]-[3] and data-layer based [4], [5].

Works in this paper is based on peer selection mechanism. As a whole, we first present a framework for streaming video from multiple peers simultaneously to a single receiver in order to achieve higher throughput. However, among the peer selection mechanisms discussed so far, all the peers are selected passively. That means whenever received a connection request, a peer should offer its service no matter whether it is willing to or not and receive no rewards. From the system point of view, it would lead to less number of peers providing service and the Qos of media stream is not guaranteed. To solve this, a novel mechanism of incentive consistent peer selection algorithm which incents a peer to offer its service is put forward in Section 3. We evaluate the algorithm through simulation in Section 4. Section 5 discusses the related work. Finally, Section 6 concludes the paper.

2. Media streaming system model

As our solution, we propose a P2P media streaming model that involves multiple sending peers in one streaming session. To get stream video from multiple senders successfully, we assume that the available aggregate bandwidth from all senders to the receiver exceeds the required video bit rate. We use most of the assumption in [7] for reference. We also assume that the limiting factor in streaming is packet loss and delay due to congestion along the streaming path, rather than the physical bandwidth limitations of the last hop.

Fig.1 shows the main function modules in a media streaming system. Most of the procedures are the same as discussed in [9]. When a peer joins the

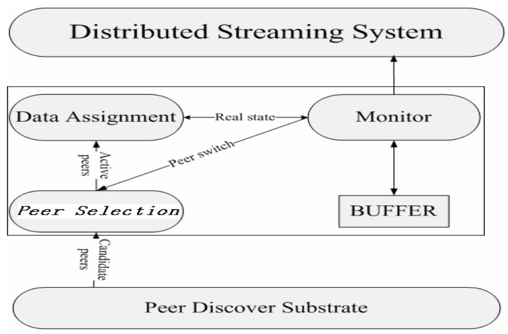

Fig. 1: Distributed Streaming System.

system, the procedure first issues a lookup request to the underlying P2P discover substrate, which returns a set of candidate peers who have the media. The selection algorithm determines the active senders who are likely to yield the best quality for this streaming session. Then, the rate and data assignment component is called to determine the appropriate rate and data portions for each active peer. Once the rates and data are assigned, two connections are established with each peer. In this paper, we emphasize on the selection algorithm.

3. A novel peer selection algorithm

Many early researches indicate that most peers' behaviors in a P2P system are related to human fancy. In this paper, we select peers based on bidding model in game theory. When a peer receives a requesting message, it first calculates an initial value based on its real-time bandwidth, delay and historical data. Other peers meet the request do this either. The request peer then tells the highest initial value to all the bidding peers. According to the initial, they compute final values and send it back to request peer. The request peer then selects the lowest N peers as service peers. In this paper, we use several terms so as to explain our mechanism more clearly:

- **Peer:** user in a media streaming session.
- **Tenderee (requesting peer):** user that asking a video service.
- **Hitter (Serving peer):** users that sending data to requesting peer.
- **Bidder (candidate peer):** users that meet the lowest requirement which is asked for requesting peer.
- **Available peer:** users that have the resource requesting peer is wanted.
- **Project:** a whole streaming session.
- **P(bidding value):** serving peer's reward value after providing a service.

We assume there are n bidders in a project. As we know, in an real economic application, the smaller P is, the more tenderee is willing to pay. This is also available on our model. The requesting peer wants to pay less while gaining best service. If bidder i is selected, the bidding value should be:

$$P_i = b_i \tag{1}$$

Assume that bidders bid on the project by rigid increment function. Then bidder j's bidding value is $B(c_j)$, c is the estimated value a bidder calculates and is given by:

$$c = \alpha * \left(\frac{\text{x}}{\text{MINSR}}\right) + \beta * \left(\frac{\text{MAXDL}}{\text{y}}\right) + \gamma * \text{z}$$

where x, y, z denote bandwidth, delay and goodness respectively; α, β, γ are their weights accordingly; Two initialized parameters: MINSR and MAXDL restrict a basic selection standard.

Different from traditional bidding model, we select numbers of peers to be hitters whereas only one hitter in traditional application. So in our model, we select N bidders whose bidding value is the lowest in a single bidding as hitters. If bidder i's bidding value is b_i, the probability it becomes hitter is equal to the probability of $b_i < B(c_j)$. The target value a bidder concerned is $\max_{b_i}(E\pi_i)$.

$$\begin{aligned} E\pi_i &= [b_i - c_i]\prod_{j \neq i} prob(b_j^* > b_i)] \\ &= [b_i - c_i][1 - prob(B^{-1}(b_i))]^{n-1} \\ &= [b_i - c_i][1 - F(B^{-1}(b_i))]^{n-1} \end{aligned} \tag{2}$$

For $\frac{\partial E\pi_i}{\partial b_i} = 0$, optimal term is:

$$\begin{aligned} &[1 - F(B^{-1}(b_i))] - (b_i - c_i)(n-1) \\ &* F'(B^{-1}(b_i))B'^{-1}(b_i) = 0 \end{aligned} \tag{3}$$

Assume B meets the symmetrical Nash equilibrium requirement: both i and its competitor are rational; the bidding values are the same while c values equal too. That means:

$$b_i = B(c_i), \quad B^{-1}(b_i) = c_i \tag{4}$$

Replace b_i, c_i in formula (3) by (4):

$$[1 - F(c_i)] - (b_i - c_i)(n-1)F'(c_i)\frac{\partial c_i}{\partial b_i} = 0 \tag{5}$$

$$F(c_i) = \frac{c_i - c_l}{c_h - c_l} \tag{6}$$

Analyze simultaneous equations (5), (6):

$$\frac{c_h - c_i}{c_h - c_l} - (b_i - c_i)(n-1)\frac{1}{c_h - c_i} \times \frac{1}{\frac{\partial b_i}{\partial c_i}} = 0$$

$$(c_h - c_i)\frac{\partial b_i}{\partial c_i} - (b_i - c_i)(n-1) = 0$$

$$\frac{\partial b_i}{\partial c_i} - \frac{(b_i - c_i)}{(c_h - c_i)}(n-1) = 0$$

$$\frac{\partial b_i}{\partial c_i} - \frac{(n-1)}{(c_h - c_i)}b_i = \frac{(n-1)}{(c_h - c_i)}(-c_i) \tag{7}$$

Deal with the differential equation (7):

$$b_i = e^{\int \frac{n-1}{c_h - c_i}dc_i}\left\{\int [-\frac{(n-1)c_i}{c_h - c_i}e^{\int -\frac{n-1}{c_h - c_i}dc_i}]dc_i + \varepsilon\right\}$$

$$= e^{\ln(c_h - c_i)^{1-n}}\left\{\int [-(n-1)\frac{c_i}{c_h - c_i}e^{\ln(c_h - c_i)n-1}]dc_i + \varepsilon\right\}$$

$$= (c_h - c_i)^{1-n}\left\{\int [-(n-1)\frac{c_i}{c_h - c_i}(c_h - c_i)^{n-1}]dc_i + \varepsilon\right\}$$

$$= (c_h - c_i)^{1-n}\left\{c_i(c_h - c_i)^{n-1} + \frac{(c_h - c_i)^n}{n} + \varepsilon\right\}$$

$$= c_i + \frac{(c_h - c_i)}{n} + \varepsilon(c_h - c_i)^{1-n} \tag{8}$$

When n=1, $b_i = c_h$, $\varepsilon = 0$, we can conclude:

$$b_i = c_i + \frac{1}{n}(c_h - c_i) \tag{9}$$

n is the number of hitters, c_h is the highest bidding value offered among hitters. Related economical theory shows that bidder turns into hitter only when it maximizes its reward. As peer provides a service, it gets the reward $(c_h - c_i)/n$ while 0 without serving. In P2P media streaming session, if request peer wants to get better Qos, it has to pay out more bidding value relatively. The bidding value is obtained by providing a service. So the more times a peer serves, the more value it can accumulate and the better Qos it can get. On the other hand, the bidding value must fit the peer's actual state. If the value is too high, the peer is less likely to be selected and get no reward; if too low, other selected peer may get more value than itself. This mechanism in a certain extent reduces the free riding phenomenon [8] in P2P system.

4. Experimental results

In this section, we first generate the topology using GT-ITM. The parameters are set as follow: thirty peers are candidate peers discovered from the underlying P2P discover substrate and the other is request peer. The rate of playback at request peer is 1Mbps. Since the media service is provided by several peers, we set the rate between candidate peer to request peer is not more than 0.5Mbps and delay is less than 50ms. To simplify the experiment, we assume no loss on the routing path.

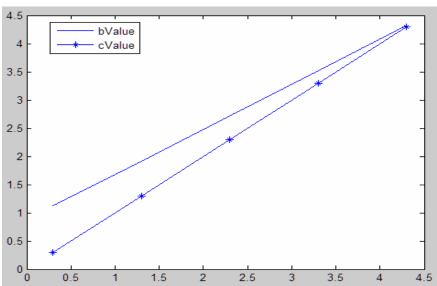

Fig.2: Peers bidding value change.

In the peer selection algorithm, we mentioned two important variables: the initial value c and the final value b. Fig.2 shows the change after first bidding. We can see that all peers' final value is higher than its initial value. This manifests the control under macro-economics which ensures all peers in the system maintain a balanced status.

We consider a peer's historical data as a significant factor that influences its service ability. This incents peers' willing to serve as many as possible. Most other peer selection mechanism doesn't consider this so as to effect the improvement of the whole media system. Fig.3 describes peers' service ability using end-to-end algorithm and our algorithm.

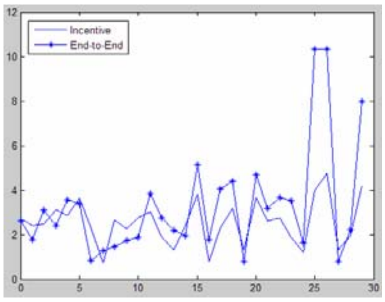

Fig.3: Peers' ability using end-to-end algorithm and our algorithm.

The abscissa is peer's ID, ordinate tells peer's ability. For peer 25 and 26, they are similar with each other at available bandwidth and delay. After end-to-end selection, their abilities are the same. But referring to experimental parameter, the historical data is different, so is their ability calculated by our algorithm. In real media streaming system, lower historical data may reflect bad behavior of a peer, such as: leave and join in frequently or without notification; less times of successful service; illusive bidding value and so on. All of which influences the Qos of the media streaming.

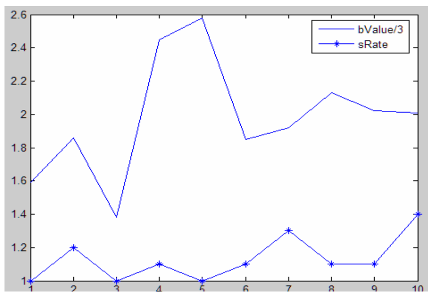

Fig.4: rates received and bidding values a request peer has to pay in experiments.

In order to get average results, we run the algorithm ten times. The number of candidate peers changes along with the amount of candidate peers. We can conclude that the more peers joined in bidding, the less that request peer has to pay. It meets the economic rules. Table 1 also proves this. Fig.4 shows average rates received and bidding values a request peer has to pay during experiments. Here, we reduce the value three times for easy view. The total rate received by request peer is more or less than 1Mbps. This can assure a steady streaming and less loss.

Exp No.	Peer No.	Bidding Value
1	8	4.77
2	6	5.99
3	9	4.14
4	5	7.36
5	6	7.74
6	10	5.54
7	9	5.75
8	9	6.38
9	9	6.05
10	10	6.03

Table 1.

5. Related work

Different from general P2P file sharing, P2P media streaming poses more stringent resource requirements for real-time media data transmission. In a highly diverse and dynamic P2P network, the question how to select sending peers for each P2P streaming session, so that the best possible streaming quality can be maintained becomes a vital factor of gaining better streaming Qos. [1] introduces three method on peer selection mechanism: random selection, end-to-end selection and topology-aware selection. Random selection selects peers for service randomly; end-to-end selection regards end-to-end bandwidth and delay as most important factor; topology-aware technique infers the underlying topology and its characteristics and considers the goodness of each segment of the path. Thus, it can make a judicious selection by avoiding peers whose paths are sharing a tight segment.

As first addressed in earlier work [6], for a media file of playback rate R_0, a single sending peer may not be able or willing to contribute an outbound bandwidth of R_0. Moreover, downloading the entire media file before playback is not the best solution, due to the potentially large media file size and long download time. Thus, an incentive mechanism is needed to provide service assurance.

6. Conclusions and future work

This paper presents a novel peer selection mechanism used in P2P media streaming service. It takes peers' social properties such as trustworthiness into consideration. This will enable Qos-sensitive user to choose the best peers that will supply the most trusted service. Experimental results indicate the peers selected by our algorithm can provide steady rate.

For the further study, we will do some experiments on how to estimate the performance between systems using different incentive mechanisms and algorithms.

References

[1] M. Hefeed, A. Hablb, Botev. Beta, PROMISE: peer-to-peer media streaming using Collect-Cast. *Technicalre port*, CS-TR03-016, Purdue University, Extended version, 2003.

[2] Y. Ma, R. S. Aygun, The Methodology of Mesh-Cast Streaming in P2P Networks. *Proceedings of the Seventh IEEE International Symposium on Multimedia (ISM'05)*, 2005.

[3] Nguyen T, Zakhor, A Distributed video streaming with forward error correction. *Hemy M,ed.Proc.of the Packet Video Workshop*, New York: IEEE Press, 2002.

[4] Y. Cui, K. Nahrstedt, Layered peer-to-peer streaming, *Christos P, ed.Proc.of the ACM NOSSDAV 2003*, New York: ACM Press, 2003.

[5] V.N. Padmanabhan, H.J. Wang, P.A. Chou and K. Sripanidkulchai, Distributing Streaming media content using cooperative networking. *Kevin A,ed. Proc.of the ACM/IEEE NOSSDAV 2002*, New York: ACM Press, 2002.

[6] D. Xu, M. Hefeeda, S. Hambrusch and B. Bhargava, On peer-to-peer media streaming. *In Proc. of IEEE ICDCS'02*, Vienna, Austria, July 2002.

[7] T. Nguyen, Zakhor, Distributed video streaming over the Internet. *In:Kienzle MG,ed.Proc.of the SPIE Conf. on Multimedia computing and Networking 2002*, Bellingham: SPIE Press, 2002.

[8] E. Adar, B.A. Huberman, Free riding on Gnutella, *Technical Report*, SSL-00-63, Internet Ecologies Area Xeror Palo Alto Research Center. Palo Alto, 2002.

[9] M. Hefeeda, AhsanHabib, D.Y. Xu and Boyan Botev, et.al., CollectCast: A Peer-to-Peer Service for Media Streaming. *ACM Multimedia* , 16, 2003.