A Statistical Prediction-based Scheme for Energy-aware Multimedia Data Streaming

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Abstract

The proliferation of multimedia-capable mobile devices and ubiquitous high-speed network technologies to deliver multimedia objects has fueled the demand of mobile streaming multimedia. A necessary criterion for the mass acceptance of mobile devices is acceptable battery life of these devices. In this paper, we explore linear prediction-based client-side strategies to reduce the wireless network interface card (WNIC) energy consumption by transitioning the WNIC to a lower power consuming sleep state. The basic idea of this strategy is to selectively choose proper periods of time to suspend communication by switching the WNIC to sleep state. A linear prediction-based time series forecasting technique is used to predict future no-data intervals. Simulation results show that linear prediction-based strategy gives better results than those based on simple averaging [6].

Key Words: linear prediction, time series forecasting, mobile multimedia, energy-aware streaming

1. Introduction

The recent proliferation of multimedia capable mobile computing devices and networking technologies has created enormous opportunities for mobile device users to communicate with one another using multimedia streams. Public venues [1] and sports stadiums [2] are deploying high speed IEEE 802.11b [3] based public wireless LAN networks. Commodity PDA devices that allow the users to consume mobile streaming multimedia are becoming increasingly popular.

A necessary criterion for the mass acceptance of mobile devices is acceptable battery life of them. There has been dramatic improvement in energy-aware design of systems, both, in terms of hardware and software. Unfortunately, advances in hardware and software are not matched by battery life. The usefulness of these mobile devices in watching streaming multimedia is restricted by battery capacity. Future trends in battery technology do not promise dramatic improvements that will make this issue disappear.

The energy consumption of the wireless network interface can be significant, especially for smaller devices. Early work by Stemm et al. [4] reports that the network interface draws significant amounts of power. Although dependent on the specific machine and wireless device, the energy consumption of wireless communication devices can represent over 50% of total system power for current handheld computing devices and up to 10% for high-end laptops. For example, a 2.4 GHz Wavelan wireless network card consumes 143mw in sleep state, and 1149mw when it receives or transmits data packets. Hence, it is important to look at techniques to reduce the energy consumed by the network interface used to download the multimedia stream.

Traditionally, network protocol optimization is a popular strategy to reduce stream fidelity. This strategy minimizes unnecessary retransmissions of stream packets, and hence reduces the amount of traffic and the total energy consumed. However, if care is not taken to return the network interface to the sleep state for as often and as long as possible, reducing the amount of transmitted date will have negligible effect on the overall client energy consumption.

Another possible strategy to reduce energy of wireless network devices is switching them to power saving mode whenever possible. As mentioned above, the energy consumption rate of a wireless network interface card (WNIC) in the sleep state and in the receiving state or idle state are substantially different. A WNIC's energy consumption rate when receiving data or when idling is substantially higher than when sleeping. A hardware-level application employing a strategy which enables switching of the WNIC to a low power consumption sleep state can allow power saving without user-visible latency. Frequent switching to a low power consumption state also promises the added benefit of allowing the batteries to recover, exploiting the battery recovery effect [5].

The basic idea of this strategy is to selectively choose proper periods of time during which to suspend communication by switching the WNIC to a sleep state. If the WNIC is suspended too often or for too long a duration at wrong periods, the users will perceive lags in the data stream. On the other hand, if the WNIC is not suspended long and frequently enough, savings in energy consumption may not be detectable. Chandra [6] demonstrates that a history-based client-side sleep time estimation strategy can be used to reduce the energy consumed by transitioning the WNIC to a lower energy consuming sleep state. In this work, we represent a statistical linear prediction-based strategy to select suspend time periods for the WNIC (time periods during which the WNIC is in the sleep state) in a server-client model when multimedia streams are being transmitted from server to client.

The remainder of this paper is organized as follows: we present a brief outline of the linear-prediction-based approach in Section 2. In Section 3 we present the experimental setup, evaluation methodologies, measurement metrics, experimental results, and comparisons of results of history-based and linear-prediction based algorithms. In Section 4, more detailed interpretation of experimental results is presented. We present some general conclusions in Section 5.

2. Linear-prediction-based Approach

In a server-client wireless network environment, data packets are transmitted as discrete bursts. Between two adjacent bursts is an interval during which there is no data being transmitted. The length of each individual no-data interval is determined by many network traffic-related factors. The series of these no-data intervals is a time series. Based on our observation, we find that the length of a no-data interval bears statistical correlation to previously observed no-data interval length values. Hence, we developed a client-side statistical linear prediction-based approach to predict future no-data interval length values based on previous observations.

Linear prediction is a mathematical operation where a future value of a time series is estimated as linear function of previously observed samples [7]. The common representation of this prediction model is

$$x'(n) = \sum_{i=1}^{p} a_i x(n-i) \qquad (2.1)$$

where $x'(n)$ is the estimated no-data interval length, $x(n-i)$'s are the previously observed values, and a_i's are the predictor coefficients. The error generated by this estimate is

$$e(n) = x(n) - x'(n) \qquad (2.2)$$

where $x(n)$ is the true value and $x'(n)$ the estimated value of the no-data interval length. A linear predictor optimizes the estimation by minimizing the estimation error. A linear prediction model has two adjustable parameters, number of poles of model denoted by the parameter p in equation (2.1) and the width of time window used for training i.e., estimating the values of the predictor coefficients. Both of these need experiments in order to choose the proper values.

In a server-client wireless network environment, if the predicted lengths of no-data intervals are frequently longer than the actual ones, the user will experience lags in the data streams being downloaded because many packets will arrive at the client's WNIC while it is in the sleep state. On this account, it is useful to add a relatively small negative bias to the sleep interval lengths predicted by the linear prediction algorithm in order to lower the data drop rate. However, if the bias is too large (in magnitude), the resulting savings in battery energy may not be detectable. The statistical linear prediction-based approach is shown to yield more accurate prediction of sleep interval lengths compared to a typical history-based prediction approach which predicts the current sleep interval length value as a simple average of previously observed sleep interval length values [6]. Thus, the negative bias that needs to be used in the linear prediction-based approach is generally smaller (in magnitude) than the one in the case of the history-based approach. This translates to greater energy savings for the linear prediction-based approach.

If a time series is truly random, we cannot observe any long term correlation. However, due to the effects of server-end network protocols, the time series consisting of the no-data interval length values is observed to exhibit long-term correlation. On the other hand, the first difference time series constructed by computing the difference of the lengths of two successive no-data intervals is observed to exhibit short-term correlation [9]. We have also investigated the application of the linear prediction-based scheme to the difference time series.

3. Experimental Setup

3.1 System Setup

The experiment system consists of a multimedia server with a wireless access point, and a mobile client with a wireless network interface card (WNIC). The mobile client has a client-side proxy. It is the client-side proxy's responsibility to transition the WNIC to a low power consumption sleep state during the predicted no-data time interval. Ideally, since no data transfers are expected during the no-data time interval, there is no loss of data.

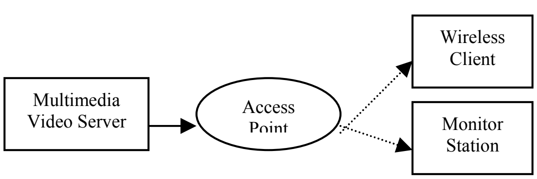

Fig 3.1. Experimental Setup

The traffic between the multimedia server's wireless access point and the mobile client is monitored by a monitoring station, which records the traffic flow in trace files. This includes the no-data interval length time series data. The multimedia stream used for our experiment is Wall video segment.

Simulation of the client-side proxy is done based on the following WNIC power consumption model. Throughout our simulation, we use the following published power parameters of a Wavelan 2.4 GHz wireless network interface card [10]: 177 mw – sleep state, 1319 mw – idle state, 1425 mw – receiving state and 1675 mw-transmit state. We assume that the transition from sleep state to idle state takes 250 µseconds and the wireless network provides a 4 Mbps throughput bandwidth.

3.2 Performance Metrics

In order to measure the efficiency of our approach, the following performance metrics are used.

- **Energy metric**: This is defined as the amount of energy consumed (in mJoules) per kilobyte received by the client side WNIC (in KBytes). The goal of our experiment is to minimize this metric. This metric measures the energy efficiency of the WNIC in terms of the energy expended for the amount of useful data it has received.

- **Drop rate**: This is defined as the percentage of data dropped due to longer-than-actual predicted no-data interval lengths. The goal of our experiment is to minimize this metric as well.

4 Experiment Results

We use the wireless traffic trace files obtained by the monitoring station to perform the simulation. If the predicted sleep interval is shorter than the actual one, the client side WNIC wakes up at the end of predicted sleep interval and transits to an idle state, ready to receive data packet bursts. If the predicted sleep interval is longer than the actual one, the client side WNIC sleeps through the end of estimated sleep interval. The data burst following the actual no-data interval is considered to be lost. The client side WNIC remains in the idle state until the beginning of next no-data interval.

For our experiments, we used the Wall theatrical trailer. The trailer is digitized to a high quality stream. The Real Player format is used for the wireless transmission of the stream. Experimental measurements of the energy metric and drop rate are made as the bandwidth of the Real Player is systematically varied.

We compare the results of the statistical linear prediction-based approach and the history-based approach described in [6]. The energy metric for the two approaches is compared for the same value of the drop rate. In order to obtain a fair comparison, the number of previous observations (number of previous actual no-sleep intervals) is set to be the same for both the linear prediction-based approach and the history-based approach.

In order to maximize the energy savings, the more accurate the prediction of the no-data interval length, the better. As mentioned previously, because of the effects of wireless network protocols, and the protocol of the wireless access point (IEEE 802.11), the time series comprising of the no-data interval lengths is a long-term correlated series. Hence, we also applied our linear predictor to the first difference time series obtained by computing the difference of two successive no-data intervals. The predicted sleep interval can be calculated from the estimated difference value using a simple formula.

The following results are obtained when Real Player is used to browse the video segment transmitted by the multimedia server. The browser station is set to 256Kbps and 512Kbps, respectively. The energy metric is plotted versus the drop rate for different values of the negative bias for both, the history-based approach and the linear prediction-based approach as shown in Figure 4.1 and Figure 4.2.

The graphs in Figure 4.1 and Figure 4.2 show that the linear prediction-based approach yields a lower energy metric than the history-based approach, for a given value of drop rate when the number of previous observations used is the same. This indicates that statistically, the linear prediction-based approach estimates sleep interval values for the client-side WNIC more accurately than does the history-based approach.

When a wireless network card is in the sleep state, it is not ready to receive data. Consequently, if the estimated sleep interval is longer than the actual one, the client-side WNIC persists in the sleep state when the data burst arrives. Accordingly, this burst of data is considered lost. It is useful to decrease data drop rate with a proper amount of negative bias added to the estimated length of the no-data interval. For a fixed value of negative bias, the more accurate the estimation, the higher the percentage of predicted sleep intervals that are shorter than the actual ones. From Figure 4.1 and Figure 4.2, we can see that for the same value of negative bias that is added to the estimation, the linear prediction-based approach results in a data drop rate that decreases more rapidly in comparison to the history-based approach. This is because the sleep interval lengths estimated by the linear prediction-based approach lie within a smaller neighborhood around the actual ones. With a relatively small magnitude of negative bias, most of the estimated sleep intervals lie within the actual ones in the case of the linear prediction-based approach.

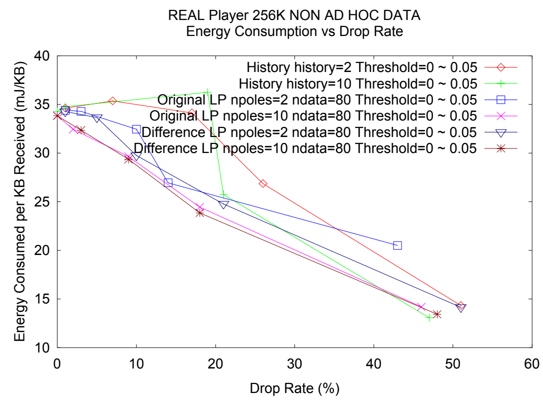

Fig 4.1. Drop Rate vs. Energy Metric Real Player, at 256 Kbps, results of history-based, linear prediction-based.

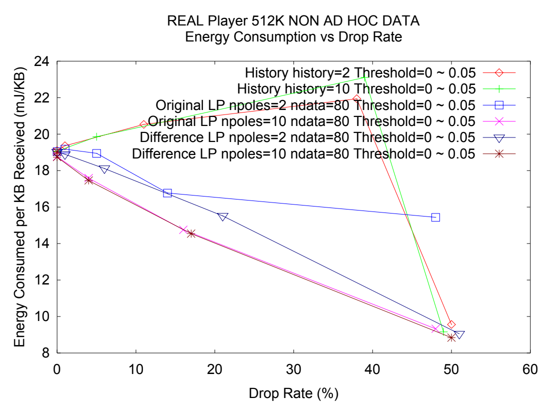

Fig 4.2. Drop Rate vs. Energy Metric Real Player, at 512 Kbps, results of history-based, linear prediction-based.

Note that the client-side WNIC sleeps through the end of estimated no-data interval. During this period of time, the power consumption is very low (approximately 177 mw). Subsequently, the WNIC transits to an idle state, during which the power consumption rate is much higher (approximately 1319 mw). Hence, the larger the magnitude of the bias that is added to the estimation, the higher the energy metric will be. In the ideal situation, the estimated no-data interval has the same length as the actual sleep interval. Note that when the bias is large enough, the WNIC will be on (in the receive state) during the entire streaming session. In this case, energy metric values of both approaches converge to the same value. From both, Figure 4.1 and Figure 4.2, it can be seen that with the same magnitude of negative bias, the linear prediction-based approach yields, simultaneously, a lower data drop rate and a lower energy metric than the history-based approach.

Results also show that when the order of linear prediction model (denoted by the parameter *p* in equation (2.1)) is very low, the application of linear prediction to the original time series comprising of the no-data interval length values gives poor results. This is the case because the original time series exhibits long-term correlation, and is best fitted by an autoregressive moving-average (ARMA) model, which is described as follows:

$$O(t) = \sum_{i=1}^{n} a_i O(t-i) + \sum_{j=0}^{m} b_j I(t-j) \quad (4.1)$$

where $O(t)$ is the output signal, and $I(t)$ is the input signal. The autoregressive (AR) portion relates the present value of the output to previous values of the output. The moving average (MA) portion relates the present value of the output to the present and previous values of the input. According to the Kolmogorov theorem [8], any autoregressive moving-average (ARMA) or moving-average (MA) process can be represented by an autoregressive (AR) process of infinite order. Note that linear prediction relates the present value of a signal to its previous values, hence it can be thought of as an AR model. In practice, when the order of an AR model is high enough, it is close to being an ARMA model [8]. This is why, when the order of linear predictor is set to a relatively high value (10 in our experiments), the prediction results are better. However, a high-order AR model entails a significant amount of computation time.

In contrast, the first difference time series, comprising of the differences of the lengths of successive no-data intervals in the original time series, is observed to exhibit short-term correlation. The application of linear prediction to the first difference time results in a lower-order prediction model that yields results comparable to linear prediction performed on the original time series.

5 Conclusions

The wireless network interface card (WNIC) of a mobile computing device accounts for a significant percentage of the overall power consumption. In this paper, we have shown how linear prediction can be used to predict the sleep time intervals for the client-side WNIC in order to reduce its energy consumption. The prediction model is trained using previously observed no-data intervals for a wireless multimedia traffic stream. Experimental results show that, for a given value of additive (negative) bias, the statistical linear prediction-based approach yields, simultaneously, a lower data drop rate and a lower energy metric when compared to the history-based approach. In fact, the history-based approach can be looked upon as a special (degenerate) case of the linear prediction-based approach where all the coefficients have the same value.

Since the original time series, comprising of the lengths of the no-data intervals, exhibits long-term correlation, it is best described by an ARMA model. In order to approximate an ARMA model with an AR model (note that linear prediction is an example of AR model fitting), the resulting AR model needs to be of substantially high order. This results in intensive computation. The application of linear prediction to the first difference time series, comprising of the differences of the lengths of successive no-data intervals, results in a lower-order linear prediction model that yields results comparable to linear prediction performed on the original time series.

References

[1] Cliff Skolnick, “802.11b Community Network List”, http://www.toaster.net/wireless/community.html

[2] Stephanie Sanborn, "Armchair Quarterbacks Go Wireless at 3com park", http://www.idg.net/english/crd_3com_259625.html, September 2000.

[3] LAN/MAN Standards Committee of the IEEE Computer Society, Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications: Higher-speed Physical Layer Extension in the 2.4 GHz Band, IEEE 3 Park Ave., New York, NY 10016, 1999

[4] Mark Stemm, Paul Gauthier, Daishi Harada, and Randy H. Katz, "Reducing Power Consumption of Network Interface in Hand-held Devices", In Proceedings of the 3rd International Workshop on Mobile Multimedia Commuincations (MoMuc-3), Princeton, NJ, September 1996

[5] Carla Fabiana Chiasserini and Ramesh R. Rao, "Pulsed Battery Discharge in Communication Devices", In Proceedings of the fifth annual ACM/IEEE International Conference on Mobile Computing and Networking (MOBICOM '99), Seattle, WA, August 1999, pp 88-95

[6] Surendar Chandra, Application-specific Network Management for Energy-aware Streaming of Popular Multimedia Formats, USENIX Annual Conference, 2002

[7] James D. Hamilton, Time Series Analysis, Princeton University Press, Princeton, NJ 1994

[8] Richard Harris and Robert Sollis, Applied Time Series Modeling and Forecasting, Wiley, 2003

[9] Peter M. Robinson, ***Time*** S***eries*** with Long Memory, Oxford University Press, Oxford; New York, 2003

[10] Paul J. M. Havinga, Mobile Multimedia Systems, PhD Thesis, Department of Computer Science, University of Twente, 2000.