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A network condition classification scheme for supporting video delivery over wireless Internet*

CHAN Siu-ping, SUN Ming-ting

(*Department of Electrical Engineering, University of Washington, Seattle 98195, USA*)

E-mail: spchan@ee.washington.edu; sun@ee.washington.edu

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Abstract: Real-time video transport over wireless Internet faces many challenges due to the heterogeneous environment including wireline and wireless networks. A robust network condition classification algorithm using multiple end-to-end metrics and Support Vector Machine (SVM) is proposed to classify different network events and model the transition pattern of network conditions. End-to-end Quality-of-Service (QoS) mechanisms like congestion control, error control, and power control can benefit from the network condition information and react to different network situations appropriately. The proposed network condition classification algorithm uses SVM as a classifier to cluster different end-to-end metrics such as end-to-end delay, delay jitter, throughput and packet loss-rate for the UDP traffic with TCP-friendly Rate Control (TFRC), which is used for video transport. The algorithm is also flexible for classifying different numbers of states representing different levels of network events such as wireline congestion and wireless channel loss. Simulation results using network simulator 2 (ns2) showed the effectiveness of the proposed scheme.

Key words: Video transport, End-to-end QoS, Wireless Internet, Network condition classification, Support Vector Machine (SVM)

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INTRODUCTION

Real-time video transport over wireless Internet faces many challenges due to the heterogeneous environment including wireline and wireless networks. Fig.1 shows a typical end-to-end video transport involving wireline and wireless networks. The video transport may suffer from many problems such as wireline network congestion and wireless multi-path fading, resulting in high packet loss-rate, and causing severe video quality degradation. To maintain the optimal video quality subject to all the constraints, end-to-end Quality-of-Service (QoS) provisioning for the wireless Internet is needed and has been an active research area. A general framework for end-to-end video transport over the wireless Internet was discussed by Zhang *et al*.(2005). However, to be effective, the techniques to combat the network impairments should be dependent on the network conditions. For example, if there are severe packet losses due to the impairments of the wireless channel, transmission power can be increased to protect the packets by maintaining a high signal-to-noise ratio. Forward Error Correction (FEC) and delay-constrained retransmission (Zhang and Kassam, 1999; Puri *et al*., 1998; Wu *et al*., 2001; Zhang *et al*., 2004) can also be used as error control mechanisms to recover the lost packets. On the other hand, if the severe packet losses are due to the Internet congestion, increasing transmission power or using error control mechanisms such as FEC and retransmission will not be effective, and actually may worsen the situation, since the retransmission may further increase the traffic and make the congestion even worse. Using video rate-adaptation may be more effective in this situation. Moreover, TCP-friendly protocols like TCP-friendly

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Rate Control (TFRC) (Floyd *et al*., 2000) will reduce the video transmission rate in order to remedy the congestion situation by sending out fewer bits or packets to the network. TFRC is a rate-based end-to-end congestion control mechanism, which uses a model for steady state TCP throughput to limit the transmission rate and assure fair behavior against competing TCP traffic (Floyd *et al*., 2000). Since the network condition is dynamic, when there is a change in the network condition, the end systems should be able to employ adaptive QoS control mechanisms including congestion control, error control, and power control to maximize the video quality. Thus, it is very desirable to be able to identify the network condition. In this paper, we propose a network condition classification scheme using Support Vector Machine (SVM) (Boser *et al*., 1992; Vapnik, 1998) as shown in Fig.2, to provide current network information for the end-to-end QoS mechanisms.

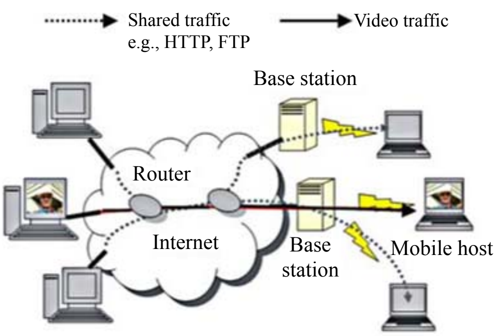

Fig.1 End-to-end video transport involving wireline and wireless networks

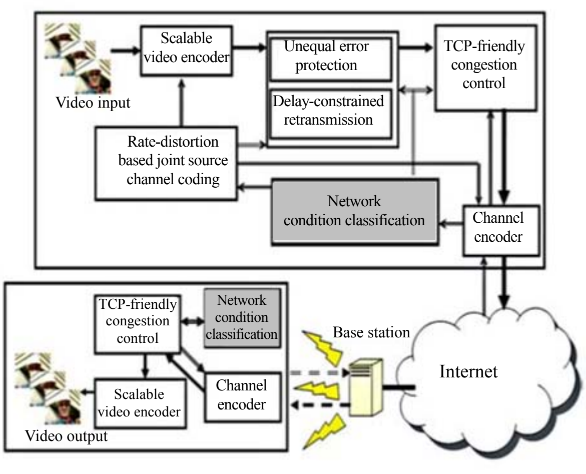

Fig.2 Network condition classification for video transport

REVIEW OF RELATED WORK

Many researchers have investigated the use of end-to-end statistics obtained at the receiver to differentiate loss nature between the wireline and wireless channels (Biaz and Vaidya, 1999; Tobe *et al*., 2000; Cen *et al*., 2003; Fu *et al*., 2003; Liu *et al*., 2003). They mainly focused on how to design an accurate loss differentiation algorithm based on a single-metric end-to-end measurement such as packet inter-arrival time, relative one trip time, or number of packet loss. Biaz and Vaidya (1999) proposed to use packet inter-arrival time to differentiate the losses. Simulation results showed that the proposed approach has a good performance when the last hop is wireless and is the bottleneck link. Later, Tobe *et al*.(2000) proposed to use the spike-train pattern in relative one trip time as an indicator of congestion. Cen *et al*.(2003) presented an end-to-end based approach to facilitate streaming over wireless. They combined packet inter-arrival time and relative one trip time for the loss differentiation and showed that the algorithm works well in many wireless situations. Fu *et al*.(2003) used a cascade of decisions with a single metric in each step to determine the network condition for supporting TCP-friendly congestion control in mobile ad-hoc networks. Hidden Markov Model (HMM) is also applied in differentiating loss nature between the wireline congestion and the wireless fading in TCP traffic (Liu *et al*., 2003).

These loss differentiation algorithms can be classified as one particular type of network condition classification, aiming to classify loss nature between two distinct network events. End-to-end loss differentiation monitors loss nature and provides information for the congestion control to react efficiently in the transport protocols. However, the end-to-end loss differentiation based on single metric (Biaz and Vaidya, 1999; Tobe *et al*., 2000; Cen *et al*., 2003; Fu *et al*., 2003; Liu *et al*., 2003) may not provide good enough accuracy for differentiating loss nature due to noisy channel measurement, as we will show in our simulation results. Besides, the existing algorithms aim to provide only simple classification of congestion and wireless channel loss. In practical network situations, multiple network events can happen simultaneously. Using single-metric end-to-end measurement may not easily identify different simultaneous network events. Therefore, there is a need to design a more sophisticated and general network condition classification mechanism, which can provide reliable information for adaptive end-to-end QoS mechanisms. Besides, it is desirable that the classification algorithm can also identify different levels of network events (e.g., the congestion level of the wireline network, and the degree of the wireless channel loss) and can classify multiple simultaneous events.

This paper aims to design a robust network condition classification algorithm using SVM based on multiple metrics, in order to classify different network events. We focus on the TFRC protocol designed for supporting video transport over the Internet. We formulate the network condition classification algorithm using SVM based on multiple end-to-end metrics and discuss the training procedure. Using the SVM, it is also flexible to define different numbers of states for different levels of network events such as wireline congestion and wireless loss. We also carry out simulations using network simulator 2 (ns2) (http://www.isi.edu/nsnam/ns) to test the performance of the proposed algorithm.

NETWORK EVENTS AND END-TO-END METRICS

In this section, we discuss the classification of different network events and then discuss the different end-to-end metrics used in the proposed network condition classification algorithm with SVM, and their importance in different network conditions.

Network events

1. Congestion

Congestion occurs when the buffers in the routers overflow which results in packet dropping according to the corresponding buffer management schemes such as DropTail (Kurose and Ross, 2003). Once the packets are dropped, transport protocols like TCP and those using TFRC reduce their transmission rate in order to resolve the congestion situation. Depending on the traffic load on a router, congestion can be classified into different levels. For example, we can define four levels of congestion as non-congestion (NC), slight congestion (SC), congestion (C), and heavy congestion (HC). Different levels of congestion have different impacts on the observations of different end-to-end metrics. For ease of explanation, in our simulations, the level of congestion is represented by the number of shared traffics over the same bottleneck link (i.e., the number of TCP and UDP shared traffics in the simulations).

2. Wireless channel loss

Due to the wireless channel impairments, packets are corrupted by different channel fading effects such as multi-path interference and shadowing. Robust and reliable wireless channel information is crucial for those end-to-end QoS mechanisms. In the simulations in this paper, different levels of wireless channel loss can be defined according to different wireless channel loss-rates (CLRs) (which represent the average packet loss-rates in the periods). For example, we can define three levels of wireless channel loss as wireless normal (WN), wireless loss (WL), and severe wireless loss (SWL). Similarly, different levels of wireless channel loss have different impacts on the observations of different end-to-end metrics. Network events of congestion and wireless channel loss can occur at the same time.

End-to-end metrics

In this subsection, we discuss different end-to-end metrics, which are used in the proposed network condition classification algorithm as the observations to classify different network events. We use only the metrics that are easily observable at the receiver.

1. End-to-end delay

End-to-end delay D_i is measured as the difference between the time t_{r_i} of the packet i being received by the TFRC receiver and the time t_{s_i} of the packet being sent out by the TFRC sender, i.e., $D_i = t_{r_i} - t_{s_i}$. End-to-end delay is increased when congestion happens due to the additional queueing delay at the bottleneck routers.

2. Delay jitter

Delay jitter J_i is measured as the absolute difference between the end-to-end delays of two consecutive packets i and j,

$$J_i = |D_i - D_j|, \tag{1}$$

where $D_i = t_{r_i} - t_{s_i}$ and $D_j = t_{r_j} - t_{s_j}$. Similar to end-to-end delay, delay jitter is increased when congestion happens, but it is not the case in wireless channel loss.

Both end-to-end delay and delay jitter are effective indicators for detecting the occurrence of congestion events in our algorithm.

3. Throughput

Throughput, Tp, is measured as the number of bits received per second at the TFRC receiver for the TFRC traffic. During congestion or wireless channel loss, Tp is reduced as the transport protocols, such as TCP and those using TFRC, reduce their transmission rate in order to resolve the congestion situation. It will be shown that Tp is also a useful indicator of the occurrence of those network events. However, on the basis of observation of throughput only, it may not be easy to discriminate the congestion and the wireless loss events.

4. Packet loss-rate

Packet loss-rate, Pl, is measured as the rate of packet loss at the TFRC receiver for the TFRC traffic. Pl is an effective metric to detect the occurrence of wireless loss events in our algorithm.

NETWORK CONDITION CLASSIFICATION

SVM was developed by Boser *et al.*(1992) and Vapnik (1998) to improve the accuracy of classifiers in machine learning and pattern recognition. The advantage of SVM is that it can achieve high accuracy with relatively small training sets. The details of SVM are discussed in (Boser *et al.*, 1992; Vapnik, 1998). To formulate the network condition classification using SVM based on multiple end-to-end metrics, we first define the number of network states N we want to classify, which depends on the different end-to-end QoS control strategies to be used. For the purpose of network condition classification, we can assign different network states (e.g., NC, SC, C and HC) to different classes in the SVM. We denote the individual network states as $S=\{S_1, S_2, \ldots, S_N\}$.

In order to apply SVM to estimate the state sequence, we need to train the SVM. First of all, feature vectors ($\boldsymbol{F}$) are extracted from the observation sequences of four end-to-end metrics as follows:

$$\boldsymbol{F}_i = [D_i, J_i, Tp_i, Pl_i],\ 1 \le i \le L, \tag{2}$$

where L is the length of the observation sequence of four end-to-end metrics, and $\boldsymbol{D}$, $\boldsymbol{J}$, $\boldsymbol{Tp}$, and $\boldsymbol{Pl}$ are the column vectors with length L for the end-to-end delay, the delay jitter, the throughput, and the packet loss-rate, respectively. SVM is then trained by using the training set of the feature vectors (Boser *et al.*, 1992; Vapnik, 1998). At this step, each feature vector is clustered into N different classes. After the training, we can obtain the model of SVM with the number of support vectors and different coefficients of support vectors used to compute the optimal hyperplane in order to separate the training samples.

The trained SVM can be used to find the estimated network state sequence $\hat{S}=\{\hat{S}_1, \hat{S}_2, \ldots, \hat{S}_N\}$, associated with the feature vectors extracted from the given testing observation sequences of different end-to-end metrics. The trained SVM model can be applied to classify different feature vectors in the testing set into different estimated network states. Moreover, we apply the three-point median filter to the estimated network state sequence $\hat{S}$, in order to remove the outliers of the estimated state sequence. We also apply the rule that the network state transition can only be possible in one single step only. The motivation is that in practical network situations, it may not be likely for an NC state to jump directly into an HC state. The transition is more likely to be from NC to SC, and then C and finally HC. By applying the rule in state transition, we can model the relational and temporal evolutional pattern of the network state transition.

RESULTS AND DISCUSSIONS

Simulations by ns2 are performed to show the performance of our proposed algorithm in different network conditions. Fig.3 shows the simulation topology and settings. In these simulations, we used TFRC (at rate of 0.2 Mbps and packet-size of 500 bytes) as the video transport protocol over the wireless Internet. Each link has capacity of 5 Mbps, with 2 ms propagation delay. Three shared TCP traffics (each at rate of 0.2 Mbps and packet-size of 500 bytes) and one UDP traffic (at rate of 0.2 Mbps and packet-size of 500 bytes) share the same bottleneck link (with a link capacity of 0.5 Mbps, and propagation delay of 20 ms) to incur different congestion situations. BS is Base Station. DropTail is used at the bottleneck link routers to manage the FIFO packet queue (Kurose and Ross, 2003). IEEE 802.11 wireless channel with a link capacity of 11 Mbps is used. The simulation time is 400 s. Different wireless CLRs (i.e. 0.02, 0.05, and 0.08) are generated by ns2 for different wireless channel conditions. The training and the testing periods are both 400 s. In the following simulations, we will first examine the performance of the proposed algorithm when only one network event occurrs in one time period. Multiple network events occurring simultaneously will be investigated in the next experiment.

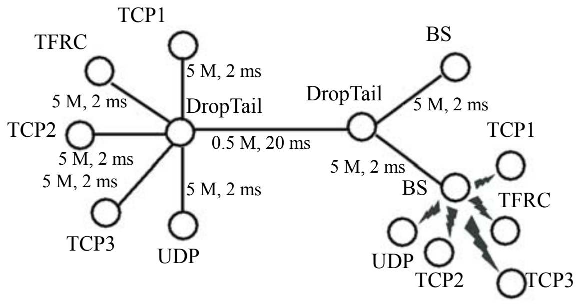

Fig.3 Simulation topology by ns2

Classifying congestion and wireless channel loss

In the first set of simulations, we investigate the performance of the proposed algorithm in classifying two individual network events (i.e., the congestion and the wireless channel loss). The events are generated by ns2 and scheduled to occur in different time periods. In this simulation, we define those network events and their corresponding settings as three different states $\{S1, S2, S3\}$. Table 1 illustrates the details of different states and their corresponding simulation settings.

Table 1 Different network states and settings

State	Network state	Simulation settings
$S1$	NC and WN	TFRC, and UDP, CLR=0.02
		Training (0~40 s and 340~400 s)
		Testing (0~50 s and 350~400 s)
$S2$	WCL	TFRC, and UDP, CLR=0.05
		Training (40~90 s and 290~340 s)
		Testing (50~100 s and 300~350 s)
$S3$	C	TFRC, UDP, and 3 TCP, CLR=0.02
		Training (90~290 s)
		Testing (100~300 s)

NC: non-congestion; C: congestion; WN: wireless normal; WCL: wireless chaneel loss

Fig.4 shows the results obtained using the proposed network condition classification and the observations of the four end-to-end metrics. It can be observed that both the end-to-end delay and the delay jitter are effective in discriminating the wireline network congestion from the wireless channel loss because there are relatively larger values in those metrics during the congestion than those during the wireless channel loss.

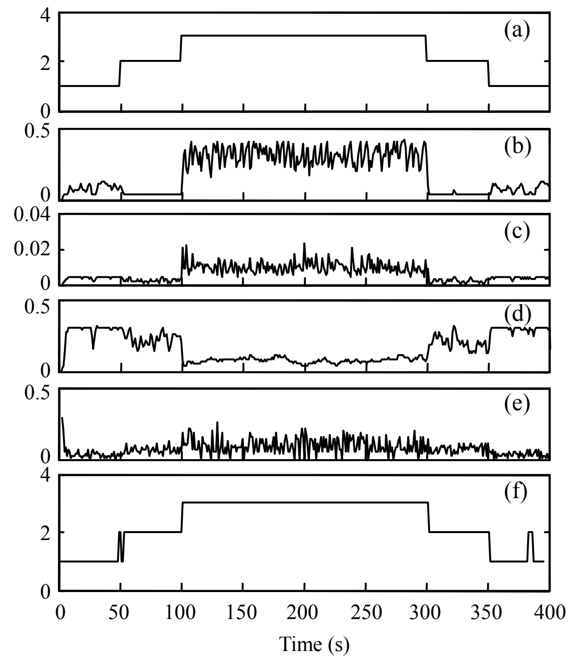

Fig.4 Testing results using the proposed algorithm to classify two individual network events. (a) Network states (Ground truth); (b) Delay of the received packets (s); (c) Delay jitter of the received packets (s); (d) Throughput at the TFRC receiver (Mbps); (e) End-to-end packet loss-rate at the TFRC receiver; (f) Estimated network states, precision=0.9722

By using the proposed network condition classification algorithm, we can estimate the network states as shown in Fig.4f and a precision of 0.9722 can be achieved. The precision is calculated by counting the number of correctly estimated states with the ground truth as shown in Fig.4a.

To compare the performance using only single metric as the observation for SVM, we performed four additional simulations using four individual metrics and the results are shown in Fig.5. The results showed that with a single metric such as end-to-end delay, or throughput, it is effective to distinguish the two individual network events: congestion and wireless channel loss, but not in the case of delay jitter or packet loss-rate. These simulation results showed that using multiple metrics can provide better performance than that of using only single metric with SVM in classifying congestion and wireless channel loss. It will be shown in later simulations that multiple metrics can provide good performance consistently under all the simulation conditions while the performance of single metric is not consistent.

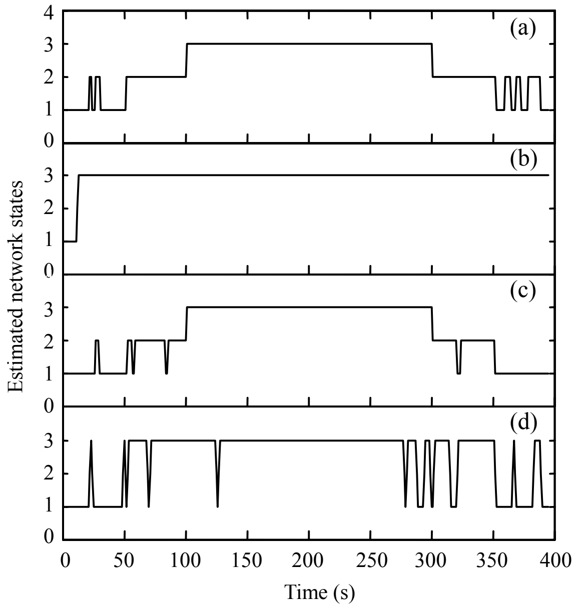

Fig.5 Testing results using only single metric to classify two individual network events. (a) End-to-end delay (Precision=0.9015); (b) Delay jitter (Precision=0.5342); (c) Throughput (Precision=0.9395); (d) Packet loss-rate (Precision=0.6861)

Classifying multiple simultaneous network events with different levels

In this subsection, we investigate the performance of classifying multiple simultaneous network events (with different congestion levels and wireless channel losses simultaneously). The motivation is that in actual network situations, multiple network events can happen at the same time. In this simulation, network events generated by ns2 are scheduled to occur at the same time period. For ease of performing simulations, we consider two different network events (i.e., congestion and wireless channel loss), each with different levels (i.e. {NC, SC, C, HC} and {WN, WL, SWL}). We define four different states {$S1$, $S2$, $S3$, $S4$}. Table 2 illustrates the details of the different states and their corresponding simulation settings. As discussed, our proposed algorithm can be applied to classify more complex network situations with more levels of events by defining more states.

Table 2 Different network states and settings

State	Network state	Simulation settings
$S1$	NC and WN	TFRC, and UDP, CLR=0.02 Training (0~40 s and 340~400 s) Testing (0~50 s and 350~400 s)
$S2$	SC and WN	TFRC, UDP, and TCP, CLR=0.02 Training (40~90 s and 290~340 s) Testing (50~100 s and 300~350 s)
$S3$	C and WL	TFRC, UDP, and 2 TCP, CLR=0.05 Training (90~140 s and 240~290 s) Testing (100~150 s and 250~300 s)
$S4$	HC and SWL	TFRC, UDP, and 3 TCP, CLR=0.08 Training (140~240 s) Testing (150~250 s)

NC: non-congestion; SC: slight congestion; C: congestion; HC: heavy congestion; WN: wireless normal; WL: wireless loss; SWL: severe wireless loss

Fig.6 shows the observations of different metrics and the estimated network states using the proposed algorithm. The proposed algorithm can achieve a precision of 0.8246 as shown in Fig.6f. Finally, Fig.7 shows the results using only single metric. By comparing the results in Figs.6 and 7, it is observed that the proposed algorithm with multiple metrics can

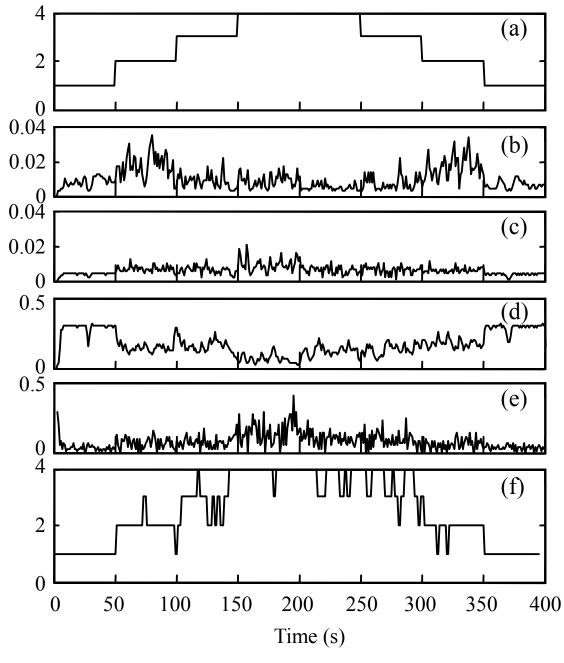

Fig.6 Testing results using the proposed algorithm to classify multiple simultaneous network events with different levels. (a) Network states (Ground truth); (b) Delay of the received packets (s); (c) Delay jitter of the received packets (s); (d) Throughput at the TFRC receiver (Mbps); (e) End-to-end packet loss-rate at the TFRC receiver; (f) Estimated network states, precision=0.8246

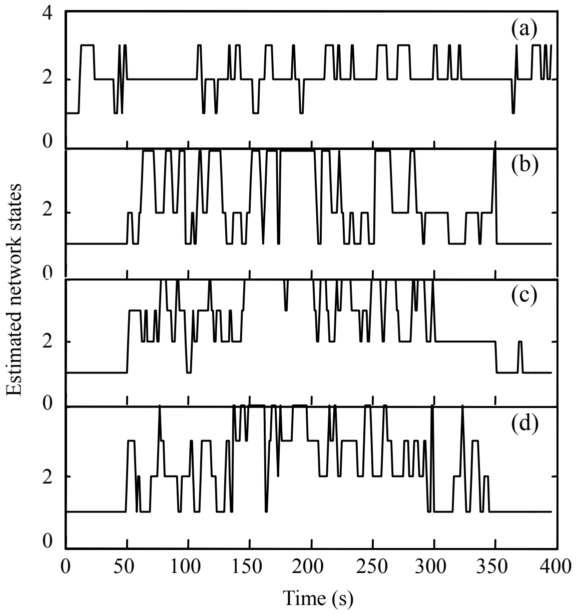

Fig.7 Testing results using only single metric with SVM to classify multiple simultaneous network events with different levels. (a) End-to-end delay (Precision=0.3894); (b) Delay jitter (Precision=0.5139); (c) Throughput (Precision=0.6380); (d) Packet loss-rate (Precision=0.5190)

outperform the scheme using only single metric with SVM in classifying multiple simultaneous network events with different levels.

CONCLUSION

A robust network condition classification algorithm using SVM based on multiple end-to-end metrics is proposed to classify different network events. The formulation and the discussions on the training are presented. The proposed classification algorithm can classify the most likely network state based on the feature vectors extracted from different end-to-end metrics observations. Simulations by ns2 were performed to investigate the performance of the proposed algorithm in different network situations such as individual network events with congestion and wireless channel loss, and multiple simultaneous network events with different levels.

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