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Wireless ad hoc video transmission: a Bayesian network-based scheme

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Abstract: A novel bandwidth prediction and control scheme is proposed for video transmission over an ad hoc network. The scheme is based on cross-layer, feedback, and Bayesian network techniques. The impacts of video quality are formulized and deduced. The relevant factors are obtained by a cross-layer mechanism or Feedback method. According to these relevant factors, the variable set and the Bayesian network topology are determined. Then a Bayesian network prediction model is constructed. The results of the prediction can be used as the bandwidth of the mobile ad hoc network (MANET). According to the bandwidth, the video encoder is controlled to dynamically adjust and encode the right bit rates of a real-time video stream. Integrated simulation of a video streaming communication system is implemented to validate the proposed solution. In contrast to the conventional transfer scheme, the results of the experiment indicate that the proposed scheme can make the best use of the network bandwidth; there are considerable improvements in the packet loss and the visual quality of real-time video.

Key words: mobile ad hoc network (MANET); Bayesian network; cross-layer; IEEE 802.11; real-time video streaming

The wireless ad hoc network is a collection of wireless nodes that self-configures to form a network, which is not dependent on the aid of any established infrastructure. The network provides a low-cost and flexible infrastructure that can be utilized by real-time video transmission. However, the dynamic characteristics associated with MANET have posed some unique challenges for video communications which include coping with tight delay constraints, bandwidth variations, frequent topology changes, and packet losses.

Many significant researches about video transmission over the wireless ad hoc network have been reported. Throughout these investigations, some schemes have been proposed to optimize transmission by a cross-layer mechanism. Such schemes mostly focus on the cross-layer between the application layer and the lower layer (MAC layer and PHY layer)[1-2]. A few other schemes that aim at the network layer or the transport layer to determine the set of network flows have minimized the congestion and found a joint optimal solution for capacity assignments[3]. Refs. [4 – 5] proposed a multi-path routing scheme; it can ensure the video quality to a certain extent with the cost increasing the route topology. Refs. [6 – 8] considered the Feedback schemes for single-hop wireless multimedia communications. However, the scheme is not suitable for the multi-hop wireless network because the packet loss worsens as the hop count increases.

Ref. [9] proposed a feedback control scheme, which is a combination of cross-layer feedback and receiver feedback. The scheme is effective in improving the ad hoc multi-hop network reliability for video transmission. However, the bandwidth upper boundary can be obtained only when the packet loss occurs. Therefore, it only rigidly adjusts the network output bandwidth from a low value to a high limit. This feedback scheme has been simulated to compare it with the proposed scheme.

In the proposed scheme, the key factor impacting the video communication quality is the network bandwidth. If the rhythm of bandwidth variations can be secured and the appropriate video data stream quantity can be sent, the best use of the network bandwidth will be obtained and the appropriate video bit rates will be encoded. This paper develops a new scheme which can predict the network bandwidth. The relevant parameters are extracted from the cross-layer mechanism and the receiver feedback method. We then construct a Bayesian network prediction model and perform Bayesian network learning. Based on the predicted results of the Bayesian network, the video encoder can be controlled to adjust the bit rates. The features of our proposed scheme are as follows:

1) By using the proposed scheme, we make the best use of the wireless network bandwidth, and obtain better quality regarding real-time video communication;

2) Due to fast convergence speed, the Bayesian network model has short-time costs in obtaining the predicted bandwidth, which is advantageous to the actual usage.

For the evaluation, an integrated video streaming system simulation is implemented where a streaming sender transmits H.264 video encoding data to a destination over a multi-hop network.

1 Scheme

1.1 System control strategy

The proposed scheme model is represented in Fig. 1. As seen from Fig. 1, the left dashed frame is the sender, and the right dashed frame is the receiver. According to Fig. 1, our proposed scheme is composed of several steps, which can be described as follows:

1) We analyze the ad hoc network and determine several main factors which impact the video communication quality. Then we extract those parameters by the cross-layer mechanism and the receiver feedback method;

2) 5-touple main influencing factors are taken as the nodes of the Bayesian network. Based on the relationships of these influencing factors, the Bayesian network structure can be determined. The Bayesian network model is applied to predict the ad hoc network bandwidth;

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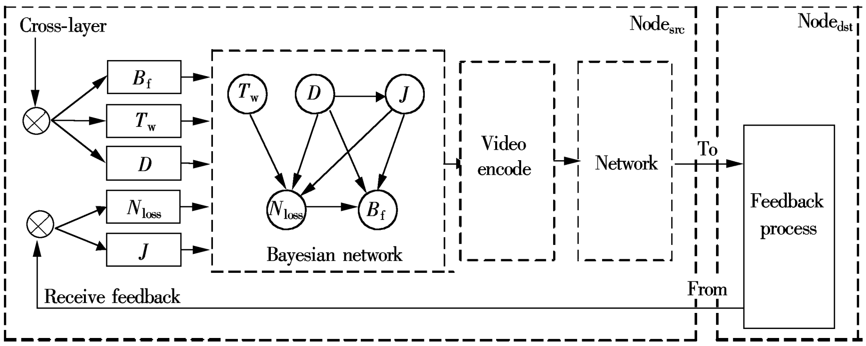

Fig. 1 System control model

3) According to the predicted bandwidth, we control the video encoder to adjust the video bitrate. The video encoder can encode and send real-time video streaming with the appropriate bitrate;

4) The relevant parameters of the communication situation are computed and fed back to the sender.

Since we need some historical data from the actual communication to execute the Bayesian network learning, we have to adopt the control strategy after some packets are sent. Before controlling the video encoder by the Bayesian network prediction outcome, the encode bitrate based on receiver feedback information is modified to prevent the ad hoc network QoS from deteriorating.

1.2 Parameter analysis and extraction

Real-time video quality is usually impacted by external conditions. The impacts are mathematically described in the following subsections in terms of the extracting method.

1.2.1 Cross-layer method

1) Throughput analysis

Assuming a multi-hop network topology with nodes set $\{A_i: i = 1, 2, \ldots, n\}$. We define $\boldsymbol{P}$ as the relevant power vector, and define $\boldsymbol{G} = \{G_{ij}\}$ between A_i and A_j as the channel gain matrix, then the signal-to-interference and noise ratio (SINR) at A_j is

$$\mathrm{SINR} = \frac{G_{ij}P_j}{\eta_j W + \sum_{k \in n, k \neq i} G_{kj}P_k} \tag{1}$$

where η_j is the noise vector and W is the full bandwidth. For the wireless link, the channel gain G_{ij} can be obtained from $G_{ij} = KS_{ij}(d_0/d_{ij})^{\alpha}$ [10], where K and d_0 are constants; d_{ij} is the distance between two communicating nodes; α is the path loss exponent; S_{ij} is the shadowing factor. According to Shannon theory, the point-to-point linker throughput is given by

$$T = W\log_2\left(1 + \frac{\mathrm{SINR}}{\Gamma}\right) \tag{2}$$

where W is the channel bandwidth and Γ is a parameter which determines the link layer design[11]. Then we can obtain the throughput formula as

$$T = W\log_2\left(1 + \frac{KS_{ij}d_0^{\alpha}P_j}{\Gamma\left(\eta_j W d_{ij}^{\alpha} + \sum_{k \in n, k \neq i} S_{ij}d_0^{\alpha}P_k\right)}\right) \tag{3}$$

It can be observed that the throughput descends as the hop count or the distance between two nodes increases.

2) Delay analysis

As seen from Fig. 2, a single-hop transmission cycle is composed of the following phases which are repeated over time, including DIFS deferral, backoff/contention, data transmission, SIFS deferral, and ACK transmission [2].

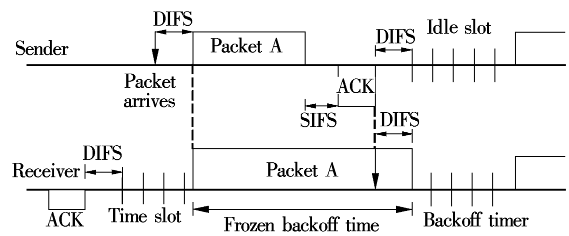

Fig. 2 IEEE 802.11 data transmission

A successful transmission time duration is equal to the sum of individual time intervals, i.e.,

$$T_{ij}^{S} = T_i^{\mathrm{DIFS}} + T_{ij}^{\mathrm{DATA}} + \alpha T_i^{\mathrm{SIFS}} + \alpha T_i^{\mathrm{SLOT}} + T_{ij}^{\mathrm{ACK}} \tag{4}$$

However, according to IEEE 802.11 standards, the station has to wait for an ACK timeout period if any packet drops out. So, we define P_{ij}^{S} as the probability of a successful transmission from A_i to A_j. The transmission duration time T_{ij} from A_i to A_j can be mathematically described as

$$T_{ij} = P_{ij}^{S}T_{ij}^{S} + (1 - P_{ij}^{S})(T_{ij}^{S} + T_i^{\mathrm{Ack}}) \tag{5}$$

Thereby, let us define T_{ij}^{w} as the total wait time of router change. The effective arrival rate of a data packet over a multi-hop network is

$$\lambda^{\mathrm{eff}} = \frac{\sum_{i \neq j}^{N} P_{ij}^{S}L_{\mathrm{frame}}}{\sum T_{ij}^{w} + \sum T_{ij}} \tag{6}$$

Using the M/M/1/Q queue results[12], the average number of packets in the transmission link is

$$L = \frac{\eta(1 - (Q_1 + 1)\eta^{Q_1} + Q_1\eta^{Q_1+1}\eta)}{(1 - \eta)(1 - \eta^{Q_1+1})} \tag{7}$$

where $\eta = \lambda^{\mathrm{eff}}/\mu$, μ is the packet processing rate, and Q_1 is the queue length. The average packet delay is $D_{\mathrm{ave}} = L/\lambda^{\mathrm{eff}}$. Thus, the detailed expression of D_{ave} is presented by

$$D_{\mathrm{ave}} = \frac{\eta(1-(Q_1+1)\eta^{Q_1}+Q_1\eta^{Q_1+1}\eta)}{(1-\eta)(1-\eta^{Q_1+1})} \frac{\sum T_{ij}^{\mathrm{w}} + \sum T_{ij}}{\sum\limits_{i \neq j}^{N} P_{ij}^{\mathrm{S}} L_{\mathrm{frame}}} \tag{8}$$

where Q_1 is a constant; therefore, the route wait time has a major impact on the network delay.

Via the cross-layer method, the information of the hop count increase[9] is obtained from the application layer and the network layer. The distance is obtained from the PHY layer.

1.2.2 Receive feedback method

An important factor which impacts real-time video streaming communication quality is the network jitter. Due to the network jitter, the steady stream becomes lumpy and discontinuous. The jitter is caused by network congestion, timing drift, frequent topology changes, distance changes, or the variations in intervals when receiving packets. The jitter can be computed at the receiver from the protocol header. For instance, we transfer a real-time video stream with RTP packets.

Let us define the synchronization time as t_i at the beginning of the communication session. Since one video frame may be fragmented in several appropriate size packets, an integrated frame can be formed from the RTP head mark segment. After receiving the last packet of the video frame, the instant time t_s is marked with the sequence number segment of the RTP head. The jitter can be computed by

$$J = \left| (t_i - t_s) - \frac{1\,000 N_{\mathrm{f}}}{r_{\mathrm{f}}} \right| \tag{9}$$

where r_{f} is the send frame rate, and N_{f} is the current number of send frames which can be obtained from the sequence number segment of the RTP head. Similarly, let us define N_{loss} as the current packet loss number which can be obtained via computing the sequence number. The packet loss rate can be computed by

$$r_{\mathrm{loss}} = \frac{\sum N_{\mathrm{loss}}}{N_{\mathrm{f}}} \tag{10}$$

In our feedback strategy, the receiver sends back the jitter and packet loss information when local jitter-buffer congestion or packet loss occurs.

1.3 Bayesian network prediction model

A Bayesian network, known as a causal model, is a directed-graph model for representing conditional independencies among a set of random variables. In a Bayesian network, an arc from node A to B can be interpreted as an indication that A causes B; i.e., A is the parent node of B. In this subsection, we first classify the parameters which are used as the training data. The Bayesian network learning is then implemented with the Bayesian network structure and the joint probability distribution among all the nodes is estimated accurately. Thus, a more precise representation of prediction relations is obtained.

1.3.1 Parameters classification

As mentioned above, the 5-touple main influencing factors can be determined and taken as the nodes of the Bayesian network, which can be described as follows:

- T_{w} is the wait time for the mobile node moving through the border line between two different router nodes, which can be obtained from the MAC layer;
- D is the distance between the sender node and the next router node, which can be obtained from the PHY layer;
- N_{loss} is the packet loss number, which can be obtained from feedback information;
- J is the network jitter, which can be obtained from feedback information;
- B_{f} is the next bandwidth value, which is predicted by the Bayesian network.

Since the parameters are sequential and not suitable for the Bayesian probability network, we should classify each parameter to make them discrete and fuzzy. According to the classification, the probability distribution of each parameter can be figured out by taking into account the historical statistical data. Tab. 1 represents the classification.

Tab. 1 Parameters classification

Parameters	Classification
T_{w}/ms	$T_1(<500)$, $T_2(\geqslant 500, <1\,200)$, $T_3(\geqslant 1\,200, <2\,500)$, $T_4(\geqslant 2\,500)$
D/m	$D_1(<100)$, $D_2(\geqslant 100, <200)$, $D_3(\geqslant 200, <300)$, $D_4(\geqslant 300, <400)$, $D_5(\geqslant 400)$
N_{loss}	$N_1(<5)$, $N_2(\geqslant 5, <10)$, $N_3(\geqslant 10, <15)$, …, $N_8(\geqslant 40)$
J	$J_1(<20)$, $J_2(\geqslant 20, <50)$, $J_3(\geqslant 50, <80)$, $J_4(\geqslant 80)$
B_{f}/(kbit · s^{-1})	$B_1(<200)$, $B_2(\geqslant 200, <300)$, …, $B_9(\geqslant 900)$

1.3.2 Bayesian network structure

According to the relationship of the above parameters, we can construct a Bayesian network as shown in Fig. 3. Every parameter is a vertex of the directed graph. The relationship of each vertex is based on statistics and prior expert experience.

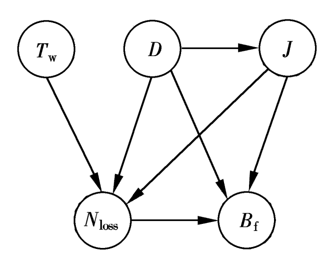

Fig. 3 The Bayesian network structure for our scheme

The relevant semantics of this directed-graph can be described as follows:

1) Since T_{w} is the wait time for the mobile node moving through the border line between two different router nodes, the parameter only impacts the packet loss of MANET, and is conditionally independent of D and J;

2) The D results from some external factors, such as topology changes and network congestion. It has no incoming arrows;

3) The B_{f} is the bandwidth prediction which is conditionally dependent on N_{loss}, D and J.

Based on these discussions, the conditional probability table (CPT) of each node can be obtained from a large amount of the training data.

1.3.3 Bayesian network learning

The Bayesian network learning is the process that obtains the posterior joint probability distribution from the prior joint probability distribution.

We define the variable set $X_i = \{T_w, D, J, N_{loss}, B_f\}$, the parent node set $P_i \in (P_i^1, \ldots, P_i^{q_i})$, $q_i = \prod_{X_i \in P_i} r_i$, and the data set D. For convenience, we define the vector parameters as $\boldsymbol{\theta}_{ij} = \{\theta_{ij2}, \ldots, \theta_{ijr_i}\}$, $\boldsymbol{\theta}_i = \{\boldsymbol{\theta}_{i1}, \ldots, \boldsymbol{\theta}_{iq_i}\}$, and $\boldsymbol{\theta}_S = \{\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_n\}$. The variable prior probability can be mathematically described as $\theta_{ijk} = p(X_i^k \mid P_i^j, \boldsymbol{\theta}_i, S^h, \zeta)$, where S^h is the structure of Bayesian network, ζ is the prior knowledge of the observer, and θ_{ijk} is the probability of $X_i = k$ when $P_i = P_i^j$.

The posterior distribution $p(\boldsymbol{\theta}_s \mid D, S^h, \zeta)$ can be deduced efficiently in a closed form under two assumptions[13]. The first assumption is that there are no missing data in the data set D. The second is that the parameter vectors $\boldsymbol{\theta}_{ij}$ are mutually independent. Based on these assumptions, the prior distribution is determined to be

$$p(\boldsymbol{\theta}_S \mid S^h, \zeta) = \prod_{i=1}^{n} \prod_{j=1}^{q_i} p(\boldsymbol{\theta}_{ij} \mid S^h, \zeta) \tag{11}$$

Assuming each vector $\boldsymbol{\theta}_{ij}$ has the prior distribution $\mathrm{Dir}(\boldsymbol{\theta}_{ij} \mid a_{ij1}, \ldots, a_{ijr})$, the posterior distribution is obtained as

$$p(\boldsymbol{\theta}_{ij} \mid D, S^h, \zeta) = \mathrm{Dir}(\boldsymbol{\theta}_{ij} \mid \alpha_{ij1} + N_{ij1}, \alpha_{ij2} + N_{ij2}, \ldots, \alpha_{ijr} + N_{ijr}) \tag{12}$$

According to the parameters learning, the prior probability distribution of the parameters is deduced as

$$p(\boldsymbol{\theta}_S \mid S^h, \zeta) = \prod_{i=1}^{n} \prod_{j=1}^{q_i} \frac{\Gamma\left(\sum_{k=1}^{r} \alpha_{ijk}\right)}{\prod_{k=1}^{r} \Gamma(\alpha_{ijk})} \prod_{k=1}^{r} \theta_{ijk}^{\alpha_{ijk}-1} \tag{13}$$

And the posterior probability distribution of the parameters is deduced as

$$p(\boldsymbol{\theta}_S \mid D, S^h, \zeta) = \prod_{i=1}^{n} \prod_{j=1}^{q_i} \frac{\Gamma\left(\sum_{k=1}^{r} \alpha_{ijk} + N_{ijk}\right)}{\prod_{k=1}^{r} \Gamma(\alpha_{ijk} + N_{ijk})} \prod_{k=1}^{r} \theta_{ijk}^{\alpha_{ijk}+N_{ijk}-1} \tag{14}$$

From the above mathematic inference, the Bayesian network prediction formula is deduced as

$$p(X_{N+1} \mid D, S^h) = \int p(X_{N+1} \mid \boldsymbol{\theta}_S, D, S^h) p(\boldsymbol{\theta}_S \mid D, S^h) = \prod_{i=1}^{n} \prod_{j=1}^{q_i} \frac{\alpha_{ijk} + N_{ijk}}{\alpha_{ij} + N_{ij}} \tag{15}$$

1.4 Encoder bitrates control

We control the encoder bitrate by adjusting the quantization parameter (QP). Fig. 4 illustrates the bitrate control mechanism which dynamically adjusts the QP to achieve an appropriate bitrate.

The QP regulates how many spatial details are saved.

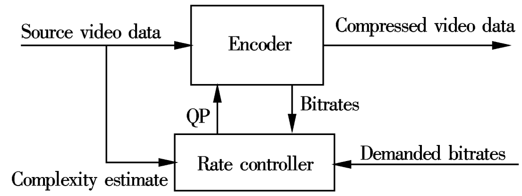

Fig. 4 Bitrates control

When the QP is very small, almost all the details are retained and the bitrate increases. As the QP increases, the bitrates drop at the cost of some quality loss. Therefore, the QP can be adjusted by the predicted bandwidth to obtain the relevant bitrate. This process does not cost superfluous time.

2 Performance Evaluations

The following comparison metrics represent the three methods separately, which are

- Normal: It is the normal communication method which has not been optimized;
- Feedback: It includes the local feedback and the receiver feedback methods, which have been proposed and implemented by Ref. [9];
- BN: It is our proposed Bayesian network strategy.

In this section, we implement performance evaluation on the effectiveness of our proposed strategy. Our simulation process has been structured in the following way. First, we simulate and compare the evaluations of the three schemes: Normal, Feedback and BN. Then, we present the true I-frame images obtained from the three methods. In addition, we present a brief conclusion about the performance comparison of the simulations.

2.1 Simulation environment

Throughout our simulation, we make use of the OPNET Modeler tool 11.0[14] with the IEEE 802.11 simulator integrated.

1) Interface condition

Real-time video input: Let a video encoder write the real-time video stream into an encode RAM buffer, and the OPNET sender program obtains it via reading the encode buffer.

Real-time video output: The OPNET receiver program obtains the integrated frame and sends it to a decode RAM buffer. Then, it notifies the decoder to decode the frame and displays the real-time image synchronously. The real-time video stream parameters are H.264, CIF, 25 frame/s and 768 kbit/s, respectively.

2) Topology condition

Fig. 5 shows the ad hoc network topology. In this scenario, D_{radius} is the wireless node transmission radius and D_{initsd} is the initial distance between node_{src} and node_{dst}. If we set the equal distance D_{ij} between each of the two router nodes, which is subject to $\{D_{ij} < D_{radius}, D_{initsd} < D_{radius}\}$, the destination node moves from the initial location to the final location following this designated trajectory. In terms of this topology, the hop count is increased from 1 to 5.

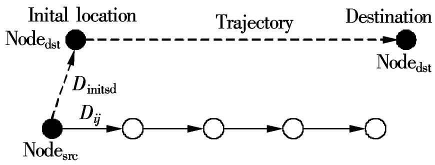

Fig. 5 A change of network topology scenario

2.2 Wireless condition

In this simulation, the major wireless parameters are listed in Tab. 2.

Tab. 2 Wireless ad hoc parameters

Parameters	Value
Ad hoc routing protocol	AODV
Active route timeout/s	5.0
Wireless LAN data rate/MBps	1
Transmit power/W	0.005
Long retry limit	4
Max receive lifetime/ms	500
Move speed/($m \cdot s^{-1}$)	2
Simulate duration/s	2 000

Each simulation runs for the duration time of 2 000 s. The mobile node move follows the designated trajectory; then Tab. 3 illustrates that the hop count increases with the topology of the mobile node changing through the field.

Tab. 3 Hop count change

Hop count	Time/s
1	0
2	670
3	1 100
4	1 570
5	1 980

As seen from Tab. 3, the hop count increases with time. According to Fig. 5, the destination node moves through the border line between two different router nodes, and the hop count increases by 1.

2.3 Simulation results

Since the feedback scheme performance relies on the intervals of feedback packets, our simulation chooses the best value from Ref. [9].

2.3.1 Packet loss

With the above conditions, we first simulate the packet loss number vs. time performance.

The packet loss is a fatal factor for video communication. The video decoder has no way to recover the source video image if some packet loss occurs, and can result in a mosaic appearance. Therefore, the number of packet losses directly impacts the video quality.

Fig. 6 shows that the packet loss of our proposed strategy is less than those of the other two strategies, especially when the hop count becomes larger. As seen from Fig. 6 and Tab. 3, the packet loss of the three methods hardly occurs when the hop count is equal to 1. When the mobile node moves through the border line between two router nodes, the number of packet losses rises rapidly, and then falls down to a relatively lower level. We also notice that the BN method converges more slowly than the other two methods. Namely, it costs more time to fall down to its relatively lower level. Occasionally, as the hop count increases, a sudden large number of packet losses emerges with the feedback method, which results from the condition when some feedback packets from the receiver are lost.

Fig. 6 only shows the packet loss number of the different methods. Since the total numbers of packets in a particular period in the three methods are different, the packet loss ratio is compared in Tab. 4.

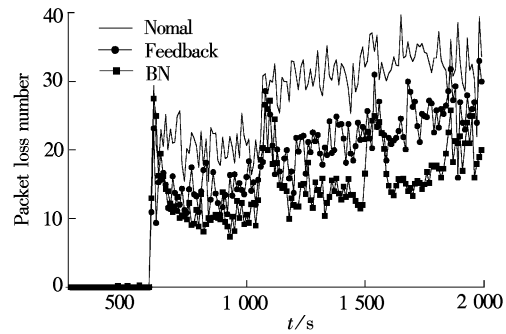

Fig. 6 Packet loss comparison of three methods vs. time

Tab. 4 The packet loss ratio comparison %

Hop count	Normal	Feedback	BN
2	39.6	27.8	22.5
3	56.2	38.3	29.8
4	68.2	47.8	35.2

From Tab. 4, we can see that the proposed BN scheme can achieve a 5.3% packet loss improvement over the feedback scheme and 17.1% over the normal scheme when the hop count is equal to 2. The BN packet loss performs better as the hop count increases.

2.3.2 Throughput

Our proposed strategy is devoted to predicting the network bandwidth, and making the best use of the actual network bandwidth. From Fig. 7, the curve of the normal method represents the actual maximal throughput. We notice that the throughput obviously descends as the route change occurs, and the feedback method maintains the level with small wavelet until the next route changes.

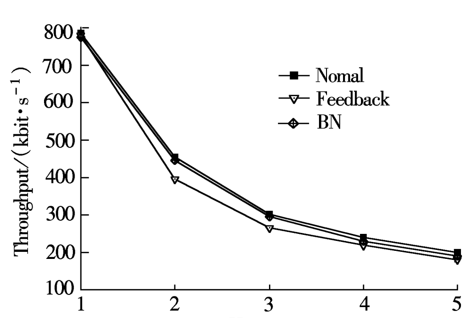

Fig. 7 Throughput comparison of three methods vs. hop count

2.3.3 Visual images

In this subsection, we choose four visual images obtained when the hop count is equal to 2, as shown in Fig. 8.

The four pictures are the source image, the image with the normal method, the image with feedback, and the im-

Fig. 8 I-frame quality comparison of three methods

age with Bayesian network. These images are I-frames with high QP values which are greater than the normal video frame. The frame is fragmentized with much more video packets than a small size frame. From these pictures, we can notice a visual performance improvement with fewer lost frames.

2.3.4 Simulation environment changing

As we know, the wireless ad hoc network depends on the environment. Different results of simulation can be obtained if we change the external environments, including wireless capability conditions and network topology conditions. In this subsection, we change some external conditions, and compute the average peak signal-to-noise ratio (APSNR) performance by comparing the received video data with the source video data frame-by-frame sequentially.

1) Changing parameter conditions

For illustration, we increase the distance D_{ij} between $node_{src}$ and $node_{dst}$, and increase the moving speed to 20 m/s. The APSNR performance vs. hop count is demonstrated in Fig. 9. Fig. 9 shows the APSNR comparison of the three methods with the dashed line representing the APSNR values after the parameters have been modified as mentioned above. We can observe that the APSNR performances decline with the modifications.

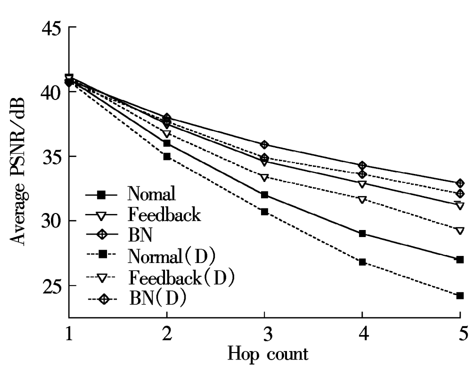

Fig. 9 Average PSNR comparison of three methods with different parameters

2) Complex scenarios

The aforementioned evaluation considers scenarios in a linear condition. For the actual non-linear usage, we simulate a more complex scenario, and hold the same parameter condition as in the above simulation, all at 20 m/s. The scenario is illustrated in Fig. 10. The destination node moves from initial location to the destination following a random curve trajectory and the hop count fluctuates without rule. The APSNR performance data with corresponding hop counts are collected with three different methods. The data are then plotted against hop count in an ascending order for comparison as shown in Fig. 11.

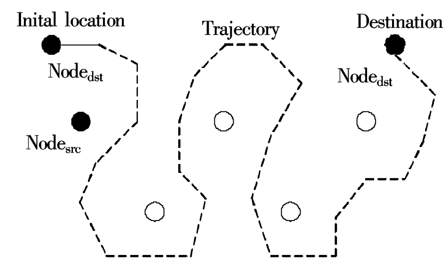

Fig. 10 A complex network topology scenario

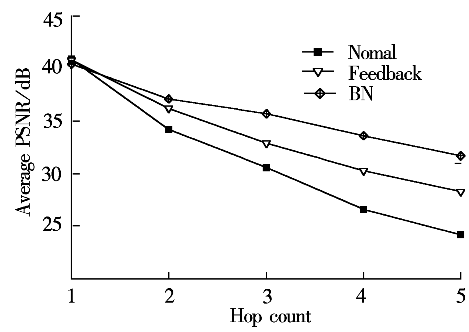

Fig. 11 Average PSNR comparison of three methods under complex scenarios

Compared with Fig. 9, Fig. 11 shows that the APSNR performance is obviously degraded at the same parameter condition. This is because the mobile node moves through the border line between two different router nodes more frequently. In other words, the frequent router switching results in network delay and jitter which impact the network bandwidth, and even the APSNR.

In fact, we can obtain different results if we implement our experiments under different environments. The simulation of this subsection illustrates that our proposed scheme can gain better performance than the other two schemes in all the different scenarios considered.

3 Conclusion

Our main objective is to obtain high quality video transmission. In order to achieve the goal, we propose a Bayesian bandwidth prediction and control scheme to make the best use of the wireless ad hoc network bandwidth. The proposed scheme integrates several key components: Bayesian network model, cross-layer, and receiver feedback. We extract the impact parameters of video communication via the cross-layer mechanism and the receiver feedback method. We adjust and control the video encoder according to the prediction results of the Bayesian network. The experiment shows that the Bayesian network has the ability of fast convergence. Based on the proposed scheme, the packet loss improvement is more than 5.3% and the quality of the received video is significantly improved.

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基于贝叶斯网络的无线 Ad Hoc 网络视频传输方法

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摘要:针对 Ad Hoc 网络的视频传输,提出了一种新的网络带宽预测及控制方案. 该方案基于跨层、接收端反馈以及贝叶斯网络等技术. 对视频传输过程进行公式化描述,从而推导出影响视频传输质量的几个主要因素,这些因素可以通过跨层机制或接收端反馈的方式获取. 根据这些影响因素,确定变量集和贝叶斯网络拓扑结构,从而构建贝叶斯网络预测模型. 预测结果作为 Ad Hoc 网络带宽,根据该带宽值来控制视频编码器,动态调节输出的实时视频流码率. 为验证该方案,对整个视频通信系统进行了仿真. 结果显示,跟传统的传输方案相比较,本方案能更好地利用网络带宽,减少了数据包的丢失,提高了实时视频质量.

关键词:无线自组织网络;贝叶斯网络;跨层;IEEE 802.11; 实时视频流

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