

# Adaptive Image Transmission with P-V Diversity in Multihop Wireless Mesh Networks

Wei Wang, Dongming Peng, Honggang Wang, Hamid Sharif

**Abstract**—Multirate multimedia delivery applications in multihop Wireless Mesh Network (WMN) are data redundant and delay-sensitive, which brings a lot of challenges for designing efficient transmission systems. In this paper, we propose a new cross layer resource allocation scheme to minimize the receiver side distortion within the delay bound requirements, by exploring application layer Position and Value (P-V) diversity as well as the multihop Effective Capacity (EC). We specifically consider image transmission optimization here. First of all, the maximum supportable source traffic rate is identified by exploring the multihop Effective Capacity (EC) model. Furthermore, the optimal source coding rate is selected according to the P-V diversity of multirate media streaming, which significantly increases the decoded media quality. Simulation results show the proposed approach improved media quality significantly compared with traditional approaches under the same QoS requirements.

**Keywords**—Multirate Multimedia Streaming, Effective Capacity, Multihop Wireless Mesh Network

## I. INTRODUCTION

MULTIRATE multimedia transmissions have popular with the rapid development of multihop Wireless Mesh Networks (WMN) [1]. of the applications over multihop WMN have spread beyond binary data transfer to delay-sensitive but loss-tolerant image applications, Quality of Service (QoS) challenges become prominent [2], since the existing multihop WMN can only provide limited service for multimedia streaming. A significant challenge is that multimedia streaming need cross layers cooperation among different network stacks for selecting the optimal transmission strategies to maximize the quality of performances in terms of Peak Signal Noise Ratio (PSNR) [3] within strict delay budget constraints. Because of the time-varying nature of wireless channels [4], it is especially difficult to develop a cross-layer design for real-time multimedia transmission systems in a multihop paradigm. In this paper, we specifically consider the optimal multihop transmission strategies for multirate image streams.

Wavelet based image compression algorithms such as [15]-[17] produce position-value differentiated information as well as layer based multirate streaming. In these multirate streams, position information is much more important than value information. Errors or packet losses in position information

lead to significant difficulties for decoding the original image, while errors in the values of magnitude are much more tolerable during decoding. This is because the position information impacts on structure of the stream, while the errors within the values are more isolated. Thus, this unequal importance will provide extraordinary opportunities for image quality improvement.

In this paper, we propose a cross-layer resource allocation scheme adapting the decoded image quality based on the multihop path conditions, delay constraints, and position-value (P-V) diversity. This is the major difference from the previous works. The exceptional gain in image quality by exploring P-V diversity can be referred to our previous researches [18] for details. Refer to Wu's Effective Capacity link model [5] and Yang's multihop delay performance study [6], the maximum achievable source traffic rate can be identified according to QoS parameters (delay bound, delay bound violation probability) and current network conditions (bit error rate on each link). Furthermore, the optimal source coding rate of Discrete Wavelet Transform (DWT) based multirate streaming is identified according to the maximum achievable source data rate. As a result, this source coding rate is optimal in the current network condition under the specific QoS constraints. This scheme simplifies the optimization problem by significantly reducing the overall parameters across application, routing, link and MAC-PHY layers, which is practical for real-time image processing applications in a time-varying wireless mesh network.

In literature, most of the previous researches have been proposed to improve multimedia quality over WLAN or WMN, but multihop challenges ave not been fully studied. The authors in [8] perform a comprehensive review of adaptive multimedia delivery researches. The authors in [7] propos a Forward Error Correction (FEC) based source-channel coding scheme to optimize multimedia quality. The research in [19] proposes Reed-Solomon (RS) coding based FEC for cross layer optimal image transmission in sensor networks with energy constraints. However, they did not consider the image position and magnitude diversity in their resource allocations. Furthermore, these studies mainly focus on single hop Unequal Error Protection (UEP), without considering multihop dynamics. Other researches such as [11]-[13] propose effective UEP optimization for delay sensitive video transmissions in WLAN, by applying different retransmissions to different media layers in the bitstreams. Although those approaches extensively explore the multi-

Authors are with the Department of Computer and Electronics Engineering, University of Nebraska – Lincoln, USA. Email: wwang@unlnotes.unl.edu

resolution nature of bitstreams, position and value information diversity is not fully explored. In [9] the authors study transport layer dynamics, and in [10] link adaptation and resource allocation as well as power control are jointly optimized to provide significant performance gains. However, these studies were mainly focusing on optimizing throughput or optimal power control without taking into considerations of application layer multimedia content. The research in [3] proposes the considerations of multimedia contents and traffic characteristics to enhance media quality gain in single hop wireless networks. They further propose a cross layer optimization scheme for multihop multimedia delivery in WMN in [4], to maximize the end to end quality for a delay sensitive video stream. The optimization of different strategies in each node incurs high complexity to the whole system. In addition, the P-V diversity is not considered in that work. The major contribution made in this paper is: first, we identify the optimal source coding rate by considering the multihop EC with low complexity; secondly, we propose an efficient resource allocation strategy to optimize the distortion reduction within the delay constraints by exploring P-V diversity.

## II. CROSS LAYER PROBLEM FORMULATION

The cross layer problem can be formulated as to optimize image quality (distortion reduction) with source coding rate constraints and QoS delay constraints. Wavelet based compression algorithms such as EZW or SPIHT compression algorithms [16] organize the positions and magnitude values of the coefficients that correspond to coefficient trees  $t$ . Although here we use tree based algorithms as examples the proposed scheme is independent of compression algorithms. It can be easily applied to other non-tree based compression algorithms such as EBCOT [17], where clusters of value information are represented as the context formation and arithmetic coding. As long as the compression algorithms can produce position-value diversity in the media streams, the proposed scheme can be easily applied.

The original image, the wavelet coefficients matrix and trees of wavelet coefficients are shown in Figure 1. After compression p-data set and v-data set are created. Specifically, symbols of positive pixel, negative pixel, isolated zeros and tree roots are outputted to the p-data set of each bit plane, while the magnitude value refinement bit is outputted to the v-data set of the current bit plane. After bit plane coding, the bitstream is of interleaving p-data sets and v-data sets with decreasing importance order. For example in Figure 2, the  $H0p$  symbol denotes position information bits of tree structure in the highest wavelet coefficients level. The  $H1v$  symbol denotes the value information bits of magnitude in the second highest level. All the position information bits  $Hip$  ( $i=0,1,2,\dots$ ) are and value information bits  $Hiv$  ( $i=0,1,2,\dots$ ) are separated.

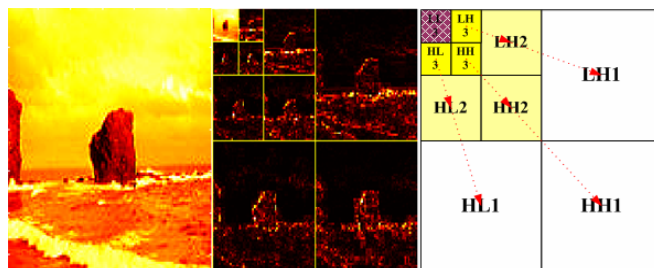


Fig. 1 The original image, the wavelet coefficient matrix and the tree structure of wavelet coefficient matrix

It is clear from Figure 2 that p-data component is more important than v-data component. The successful decoding for a single p-data component depends on the successful decoding of all previous p-data components. The successful decoding of a single v-data component depends on the successful decoding of both all previous p-data components and v-data components. So, general design guideline for the proposed efficient image delivery over WMN with distortion optimization can be formulated as follows: p-data components have relatively higher protection levels than v-data components. For p-data component set or v-data component set, the preceding components deserve higher protection than later components. Thus valuable resources and efforts are used in important components, and the image transmission quality can be enhanced while the overhead is reduced.

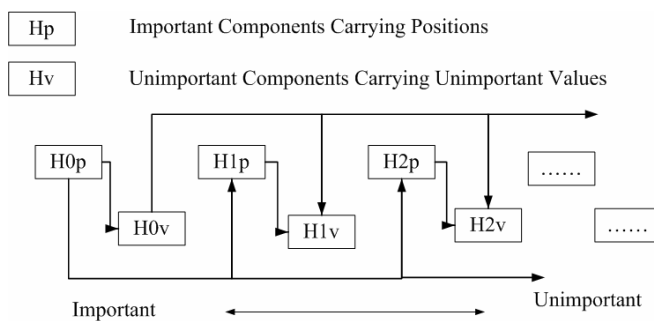


Fig. 2 Structure of the inter-dependent image bitstream

The expected decoding quality (distortion reduction) can be easily expressed as follows. Let  $L$  denote the total layers of bitstream,  $\Delta_p(j)$  denote the distortion reduction [12] of the  $j^{\text{th}}$  p-data component, and  $\rho(p, j)$  be the corresponding average packet loss ratio. In a way similar to [13], we can let  $\rho(p, i+1) = 1$  to denote the end of compressed embedded multi-resolution bitstream. Thus the expected contribution of all the p-data components for reconstructed image can be expressed in the follow equation:

$$\mathcal{E}[\Delta_p] = \sum_{i=0}^{L-1} \left( \sum_{j=0}^i \Delta_p(j) \right) \left( \prod_{j=0}^i (1 - \rho(p, j)) \right) \rho(p, i+1) \quad (1)$$

In a similar way, we can express the distortion reduction of v-data components. Let  $\Delta_v(j)$  denote the distortion reduction of the  $j^{th}$  v-data component, and  $\rho(v, j)$  denote the corresponding average packet loss ratio of that v-data component. The expected distortion reduction of all the v-data is expressed as:

$$\varepsilon[\Delta_v] = \sum_{i=0}^{L-2} \left( \left( \sum_{j=0}^i \Delta_v(j) \right) \cdot \prod_{j=0}^{i+1} (1 - \rho(p, j)) \right) \cdot \prod_{j=0}^i (1 - \rho(v, j)) \cdot \rho(p, i + 1) \quad (2)$$

From these equations it is easy to see that the distortion contributions of p-data components are much more important than those of v-data components. This is because the decoding of v-data depends on the decoding of p-data. This observation also shows the design philosophy that by putting more effort on p-data component, the quality can be enhanced. The total distortion reduction  $\varepsilon[\Delta]$  can be expressed as the sum of all the distortion reductions of p-data and v-data  $\varepsilon[\Delta] = \varepsilon[\Delta_p] + \varepsilon[\Delta_v]$ .

Each packet loss ratio  $\rho$  can be approximated by packet loss ratio. If the component size is larger than the segmentation frame size, assume  $Np$  to be the segmented packet count of that component. In a way similar to [14], each  $\rho$  can be easily approximated as follows in terms of measured Frame Error Rate (FER) on each link, and  $M$  is the redundancy level of that component:

$$\rho = 1 - \prod_{i=1}^h (1 - FER_i^M)^{Np} \quad (3)$$

Where the FER on the  $i^{th}$  link can be straightforwardly expressed by the BER measured on that link:

$$FER_i = 1 - (1 - BER_i)^{L_{DATA}} \quad (4)$$

From this equation we can see that, by increasing the redundancy level, the average loss ratio of corresponding component decreases. Thus, redundancy level is an effective approach to combat with severe environment in wireless channels. However, different part of image bitstream has different perceptual importance. Errors in shape and position information (p-data components) lead to high difficulties for reconstructing the original image, while errors in packets consisting of pixel or wavelet coefficient magnitudes are more tolerable during transmission and decoding. This is because the former information impacts on multiple packets of image data while the error with the latter is isolated. This position-value of magnitude diversity provides extraordinary opportunities for efficient image transmissions over WMN.

Thus the optimization problem can be re-formulated as follows: acquire the optimal solution vector for each component with assigned redundancy level  $M$  to maximize the expected distortion reduction:

$$\begin{aligned} & [M(0, p), M(1, p), \dots, M(L-1, p) \\ & M(0, v), M(1, v), \dots, M(L-2, v)] \\ & = \operatorname{argmax} (\varepsilon[\Delta]) \end{aligned} \quad (5)$$

where the source coding rate  $R$  is subject to the maximal source coding rate constraint  $R_{\max}$ .

$$R \leq R_{\max} \quad (6)$$

and the source coding rates can be expressed in terms of redundancy levels  $M$  and maximal supportable traffic rate  $u_{opt}$ :

$$R = \sum_{i=0}^{L-1} M(i, p)H(i, p) + \sum_{i=0}^{L-2} M(i, v)H(i, v) \quad (7)$$

$$R_{\max} = u_{opt} \times (D_{\max} + D_{image}) \quad (8)$$

The optimization problem can be easily solved by a simplified Genetic Algorithms (GA). A lookup table based implementation can be applied for further fast execution, with periodic update of solution vectors. The maximum source coding rate with specific QoS requirements can be translated into optimal traffic rate, which in turn can be acquired by given delay bound violation probability, delay bound  $D_{max}$ , image transmission delay, observed packet-in-service sample  $S_n$ , observed queue length  $Q_n$ , observing window size  $N$ , which will be discussed in the next section. Figure 3 illustrates the algorithm of acquiring the optimal redundancy level  $M$  for each component according to QoS constraint parameters including delay bound and delay bound violation probability, the whole image transmission delay. The packet-in-service can be observed from image stream and queue size can be observed directly from the buffer. Through this non-trivial simplification, a very simplistic GA can be designed with fitness function shown as follows, where  $\varepsilon[\Delta]$  is the expected distortion reduction of reconstructed image.

$$F = \varepsilon[\Delta] \quad (9)$$

The proposed Genetic Algorithm to solve this optimization problem can be formulated as follows:

**Input:** The distortion reduction for component, component size, delay bound, delay bound violation probability, optimal traffic rate (which will be discussed in the next section),

**Output:** redundancy level of each component.

(A): Initialization for gene binary coding and decoding: Each element in the solution  $[M(0,p) M(1,p) M(0,v) M(2,p) M(1,v) \dots M(L-1,p)]$ , is coded as a gene, thus each possible solution for redundancy level is coded as a chromosome gene sequence, where  $i=0,1,2,\dots,L-1$ , denoting the component levels;  $j=p,v$  denoting the type of that component. Select the population space size  $POP\_SIZE$  and maximal generations  $G\_MAX$ , and random create the first generation with the specified population size.

(B): Gene robustness enhancement according to  $p-v$  diversity: In each chromosome, sort the random generated redundancy level genes according to distortion reduction measurement and the importance level of each component. Thus high redundancy level is assigned to important component, leading to performance improvement of GA.

(C) Evaluate the fitness of each chromosome and sort the chromosome in descending order according to their fitness values.

(D) Elitism Parents Crossover in the current population: By denoting the  $k$ -th chromosome's fitness function as  $F(k)$ , ( $k=1,2,\dots, POP\_SIZE$ ), the probability that one chromosome crossover with others is expressed as follows:

$$p(k) = \frac{F(k)}{\sum_{k=1}^{POP\_SIZE} F(k)} \quad (10)$$

Thus randomly switch chromosomes to produce a new generation of population with the same size.

(E) If maximal generation count  $> G\_MAX$ , then go to (F). Else go to (B) to refine the newly produced generation of population.

(F): Output the best chromosome in the final population, with the maximum fitness value.

Considering fast execution, a lookup table based Adaptive Rate Optimization Unit (AROU) is designed. The inputs to the AROU are image streams, measured distortion reduction as well as component size, QoS parameters such as delay bound, delay bound violation probability and the observed queue length. Specifically, desirable transmission redundancy parameters for different image component patterns for queue length conditions are pre-calculated and stored in a cache bank. The cache bank serves as a lookup table cache for AROU, where pre-calculated GA based solution vector values of typical image patterns are stored. Component distribution and the associated distortion reduction for transmission in variable network conditions constitute a serial of patterns, and

the pattern can be determined unambiguously by components count and size, distortion reduction as well as the current network condition (queue length). The typical mapping sequences are offline trained. Given delay bound and delay bound violation probability requirements, queue length and packet in service probability can be both measured from network. Thus the optimal redundancy level  $M$  of each image component can be directly consulted from the lookup table.

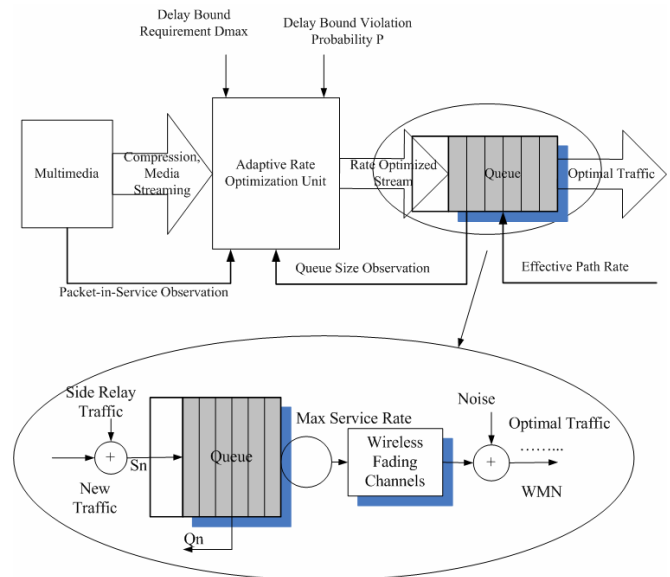


Fig. 3 Dataflow of matching maximal traffic rate to optimal image quality

### III. MAXIMAL SOURCE CODING RATE

The optimal source coding rate can be translated into the maximal source traffic rate with QoS delay bound and delay bound violation probability constraints in a multihop path. Each node in WMN has the same combined arrival rate  $\mu$  of new and relayed traffic in the steady network state. Furthermore, let  $Q_n$  denote the instantaneous link layer queue length at the  $n$ -th sampling interval. The queue length depends on the time-varying wireless channel condition and the incoming source traffic rate determined by the packet transfer process of the previous node. By directly mapping the key physical layer parameters to the data link layer delay performance and delay bound violation probability, the concept of effective capacity (EC) has been recently proposed as a simple but accurate data link layer model for QoS support under flat-fading and frequency-selective fading radio channel conditions [5]. Details of EC model are described in [5] and [6]. For a single-hop connection, the probability that delay  $D$  exceeds a delay bound  $D_{max}$  is approximated as follows according to [5]:

$$P\{D > D_{max}\} = \gamma \cdot e^{-\theta \cdot D_{max}} \quad (11)$$

In this equation  $\gamma$  and  $\theta$  are functions of the combined traffic rate  $\mu$  at the source node. Specifically,  $\gamma$  is the probability of a

nonempty queue and  $\theta$  is the decay rate of delay bound violation probability [5]. They are both related to time-varying wireless channel conditions and incoming source traffic rate.

Recently Chen and Yang in the research [6] extend the EC model of [5] to analyze the delay violation performance of a multihop path in a WMN. They derive a lower bound of delay-bound violation probability. Let random variable  $D_i$  ( $1 \leq i \leq h$ ) denote the steady state delay experienced by a typical packet at hop  $i$ . For a routing path with  $h$ -hop, the lower bound of delay-bound violation probability can be approximated according to [6] by the following equation:

$$P\left\{\sum_j D_j > D_{\max}\right\} = 1 - \sum_{j=1}^h C_{h-1}^{h-j} \cdot (1-\gamma)^{h-j} \cdot \gamma^{j-1} \cdot [1 - e^{-\theta \cdot D_{\max}} \left(\sum_{i=1}^{j-1} \frac{(\theta \cdot D_{\max})^{i-1}}{(i-1)!} + \frac{\gamma \cdot (\theta \cdot D_{\max})^{j-1}}{(j-1)!}\right)] \quad (12)$$

In a way similar to [5], the QoS parameters  $\gamma$  and  $\theta$  can be accurately estimated by taking a large number  $N$  of samples. Here let  $S_n$  indicate whether a packet is in the server at sample  $n$ , Also let  $T_n$  denote the remaining service time of the packet in the server. Assuming a fluid source traffic model, the size of a packet is infinitesimal and  $T_n = 0$  compared with queuing delay  $Q_n/r_n$ , propagation delay over a single wireless hop is negligible

$$\hat{\gamma} = \frac{1}{N} \sum_{n=1}^N S_n \quad (13)$$

$$\hat{\theta} = \frac{\hat{\gamma} \times u \times N}{\sum_{n=1}^N (Q_n(u, r_n))} \quad (14)$$

The end-to-end delay performance over multihops can be obtained by replacing  $\gamma$  and  $\theta$  with these estimated values, The instantaneous queue length is determined by source traffic rate and effective service rate. Assume the critical link effective capacity is the bottleneck of the effective path capacity of a path, in the steady state the queue length of the source node is a sufficient indicator for wireless channel conditions on each link of one path. The delay bound violation probability can thus be easily expressed as a function of source traffic rate  $u$ , packet-in-service probability  $S_n$ , measured queue length  $Q_n$ , observing window size  $N$ , and delay bound requirement  $D_{\max}$ :

$$P\left\{\sum_{i=1}^h D_i > D_{\max}\right\} = \text{func}(u, Q_n, S_n, N, D_{\max}) \quad (15)$$

So from this equation, given delay bound and delay bound violation probability, by observing window size  $N$ , and

packet-in-service probability  $S_n$  as well as queue length  $Q_n$ , the maximum serviceable source traffic rate  $u_{opt}$  supported by the current multihop path can be easily determined by the reverse function of (15). Thus the maximum of source traffic rate and the optimal source coding rate are both identified, which serve as the constraint in the cross layer resource allocation problem.

#### IV. SIMULATIONS

In the simulation section, we show the identified maximum source traffic rate under QoS constraint and the improved image quality expectation of EC adaptive P-V based cross layer resource allocation approach. The performance is compared with traditional non EC adaptive approach and traditional layer based UEP approaches of EC adaptation. Simulation parameters are stated as follows. The path is composed of three hops and the capacity is 100kbps. We assume routing and scheduling have assured the uniform transmission rates on each link in a path. The average BER on each link is configured as  $1e-4$ . An image with  $128 \times 128$  pixels with 8bpp is transmitted in a three hop WMN. To reduce GA optimization complexity, only four bitplanes' p-data redundancy levels are optimized from Most Significant Bit (MSB) because of their significant importance; v-data and p-data in low bitplanes are with unit redundancy level. Other parameters are the same as [5] and [6]. The topology of the WMN is shown in Figure 4.

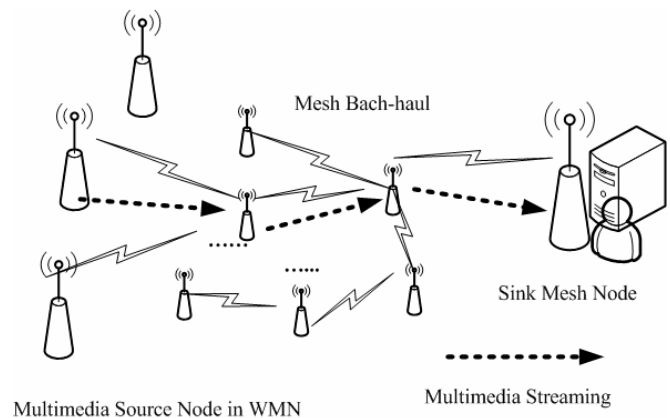


Fig. 4 WMN simulation topology

Figure 5 illustrates the queue lengths at the source node with different source traffic rates and a stable 100kbps effective path capacity. From this figure it is clear that, for the same effective path capacity, the queue length is nonlinear proportional to source traffic rate. The queue length is very low with low traffic rate; however, increasing traffic rates lead to abrupt non-linear queue length increasing, which in turn severe the multihop delay performance. The results shown in this figure is quite close to the results in [5], showing the link layer model used in this simulation is relative accurate.

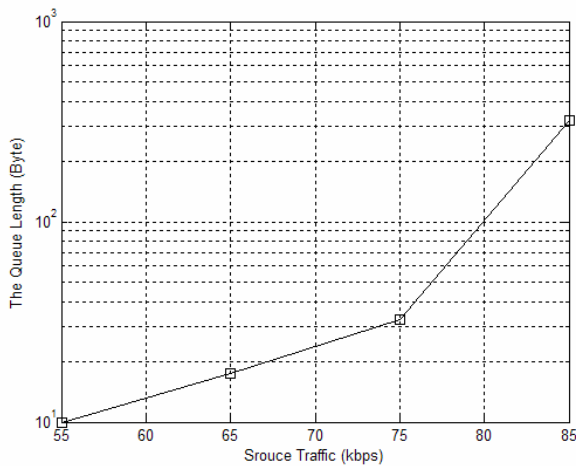


Fig. 5 Queue Length of source node at different traffic levels

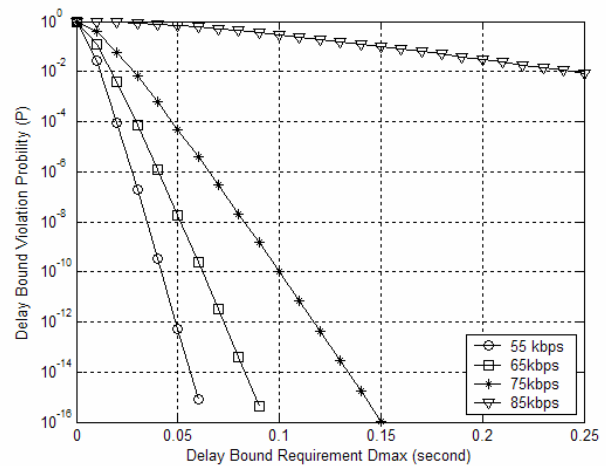


Fig. 6. Multihop delay performance for different source traffic rates

Figure 6 illustrates the multihop delay and delay violation probability performance for different source traffic rates. The performance curves for  $u=75\text{kbps}$  and  $u=85\text{kbps}$  in this figure are very close to the results in [6]. From this figure we can see, the delay bound violation probability is very sensitive to source traffic rate. The multihop delay performance is decreasing with the increasing of traffic rate. The results in this figure intuitively match the queue length results in Figure 5. In Figure 6, the x-axe is the delay bound requirement and the y-axe is the delay bound violation probability. To find the field meeting the requirement of these two QoS parameters, one point can be located in this figure by crossing of delay bound line and delay boundary violation probability line. The source traffic rate curve passing this point is the maximum supportable source traffic rate under these QoS parameter constraints. All points located in the left-down rectangle of that point also meet the QoS requirements with lower maximal source coding rates.

The maximum supportable traffic rates with delay bound violation probability 0.0001 and different delay bound requirements are shown in Figure 7. It is the upper bound of source traffic meeting the delay bound and delay bound violation probability QoS requirements. From this figure we can see, when the delay bound becomes loose, the maximum source traffic rate supported by network becomes larger. This shows the tradeoff between QoS and throughput: with a higher QoS requirement, the maximum throughput that can be guaranteed by network is reduced, and vice versa.

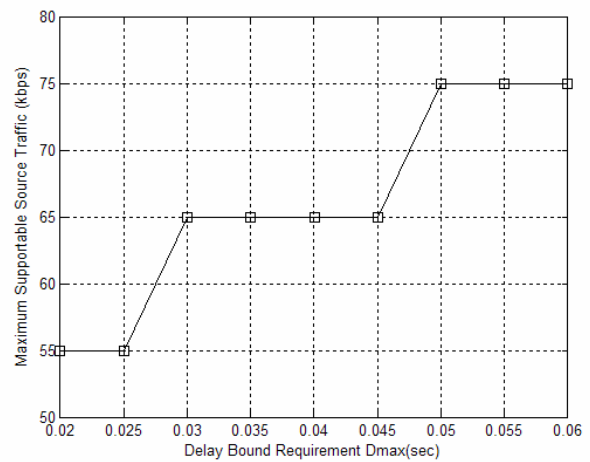


Fig. 7 Maximum supportable source traffic rate with different delay bounds

The unequal importance position information and value information is shown in Figure 8. And Figure 9 quantifies reconstructed image PSNR for erasing different p-data or v-data components by wireless channels. These figures support the validity of the proposed P-V oriented cross layer optimization to improve image quality via a smart resource allocation strategy. V-data components can not make significant contribution to image distortion reduction without the depending p-data components. This is because p-data components contain bitstream structures and position information, while v-data components contain only magnitude value information. Erasing p-data components in any bit plane will cause serious distortion, especially erasing p-data components near Most Significant Bit (MSB) bit-plane. Even in bit-planes near Least Significant Bit (LSB), p-data components still have 6dB-8dB more perception importance than v-data components. The loss of p-data components causes unacceptable image noise and visual effect even near LSB planes. On the other hand, erasing v-data components by wireless channel even near MSB bit plane can still provide acceptable visual effect of reconstructed images.

Figure 10 shows that the Packet Loss Ratio (PLR) decreases with more redundancy levels applied to the large frames. This effect is more significant in high BER levels. In relatively good channels where few errors occur, the redundancy may be pure overhead; however, in noise wireless channels, adding redundancy may significantly reduce the final error probability of each frame.

Figure 11 shows the redundancy level diversity gain for different frame lengths. From this figure we can see, redundancy level diversity achieves better performance for all the frame lengths, while the PLR performance without redundancy level deteriorate significantly when the frame length increases.

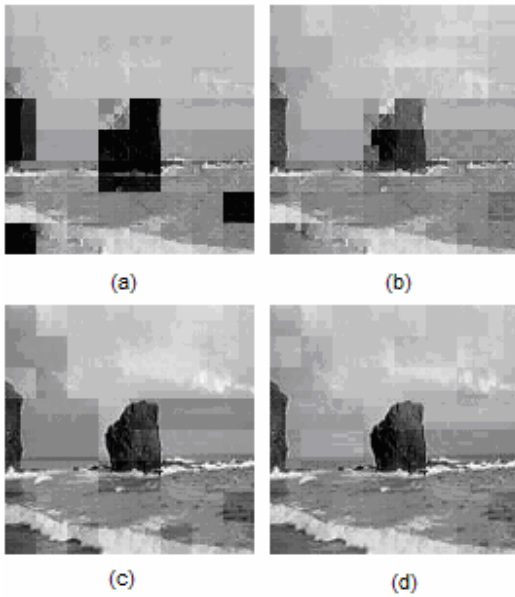


Fig. 8 Reconstructed images when losing different p-data-v-data components in different bit-planes. (a): losing p-data component in bit-plane 1, PSNR = 15.7399 dB; (b): losing p-data component in bit-plane 3, PSNR = 22.9243 dB; (c): losing v-data component in bit-plane 1, PSNR = 22.5890 dB; (d): losing v-data component in bit-plane 3, PSNR = 31.2512 dB

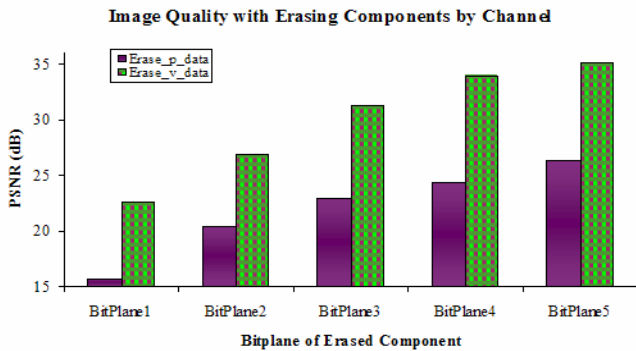


Fig. 9 Reconstructed image quality with erasing different p-data or v-data components in different bit-planes

Figure 12 shows the effective gain of redundancy levels in multihop PLR performance. With the hops increase, accumulated error of each frame increases significantly without redundancy level diversity. With redundancy level diversity applied to multihop scenarios, the end to end PLR

performance is significantly improved. The more hops in a path, the better performance the redundancy level diversity level can achieve.

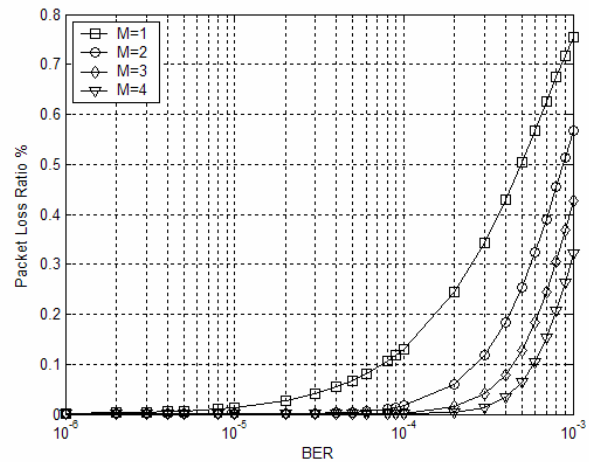


Fig. 10 Average packet loss ratio for different redundancy levels. Hop=1, Frame length equals 1400bytes here

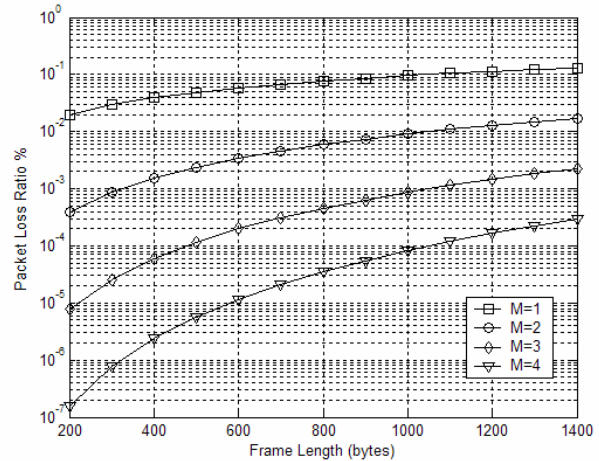


Fig. 11 Average packet loss ratio for different redundancy levels. BER is 1e-4, hop=1, Frame length is variable here

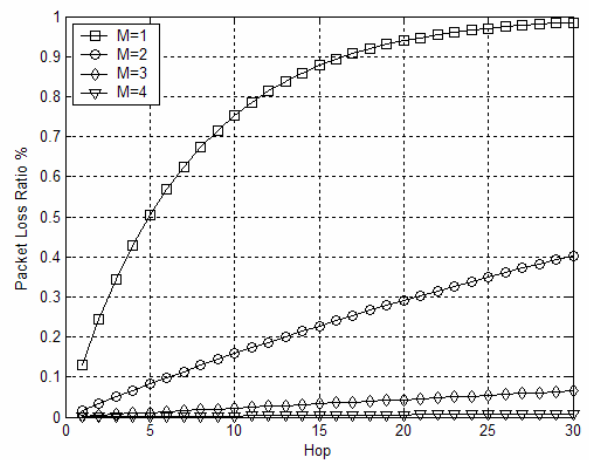


Fig. 12 Average packet loss ratio for different hops with frame length 1400bytes and variable redundancy levels. BER is 1e-4 here

Figure 13 shows the quantitative analysis of expected image quality and delay bound constraints. In this figure, the non-optimal approach uses fixed source coding rate without considering effective capacity (EC), thus the PSNR is very low compared with the other two optimized approaches. The layer based resource allocation scheme reduces the distortion by considering the maximum supportable traffic rate. Thus the source coding rate is maximized and distortion reduction is improved. In some cases the non-optimal approach happens to achieve the maximum supportable traffic rate, and then the delay-quality performance of the two schemes are the same. In other situations, the EC aware approach always achieves higher PSNR value than non-optimal approaches, because network delay budgets are more efficiently utilized. The P-V oriented resource allocation approach optimizes the redundancy level of important p-data components jointly, achieving significantly improved image quality compared with the other two schemes within the same delay budgets. The reasons of this improvement are explained as follows. By considering the EC, the optimal source coding rate can be identified. Thus network resources can be more efficiently utilized. On the other hand, by exploring intra-image position-value diversity, network resources for reliable protections are more efficiently allocated in the image bitstream.

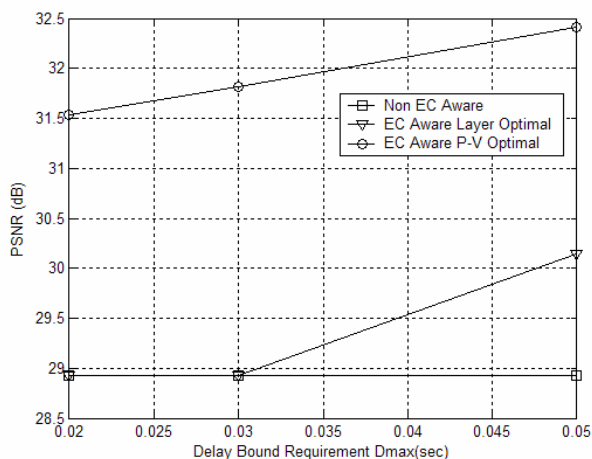


Fig. 13 Expected image quality for different of delay bound requirements

## V. CONCLUSION

In this paper, we have proposed an adaptive image transmission scheme to optimize image quality in a multihop WMN, while considering QoS constraints including delay bound and its violation probability. Specifically, the maximum supportable source traffic rate under specific QoS parameters including delay bound and delay bound violation probability and multihop path condition is efficiently identified and a practical approach for approximating the optimal source coding rate is studied. Then a P-V oriented cross layer resource allocation optimization scheme is proposed to maximize the expected image quality within the QoS requirements, which shows significant quality gain.

Simulation results show the proposed approach significantly enhances image quality by more efficient resource allocation within the delay bound and delay bound violation probability requirements,

## REFERENCES

- [1] I.F.Akyildiz, X.Wang, "A survey on wireless mesh networks," *IEEE Communications Mag.*, vol.43, no. 9, pp.23 - 30, Sept.2005
- [2] R.Bruno, M.Conti, E.Gregori, "Mesh networks: commodity multihop ad hoc networks," *IEEE Communications Mag.*, vol.43, no. 3, pp.123 - 131, Mar. 2005
- [3] M. van Der Schaar, Sai Shankar N, "Cross-layer wireless multimedia transmission: challenges, principles, and new paradigms," *IEEE Trans. on Wireless Communications*, vol.12, no. 4, pp.50 - 58, Aug.2005
- [4] Y.Andreopoulos, N.Mastrorade, M.Van Der Schaar, "Cross-Layer Optimized Video Streaming Over Wireless Multihop Mesh Networks," *IEEE J. Sel. Areas in Commun.*, vol.24, no. 11, pp.2104 - 2115, Nov.2006
- [5] D.Wu, R.Negi, "Effective capacity: a wireless link model for support of quality of service," *IEEE Trans. Wirel. Commun.*, vol.2, no. 4, pp.630 - 643, Jul 2003
- [6] J.Chen, Y.Yang, "Multi-hop Delay Performance in Wireless Mesh Networks," in *Proc. GlobalCom 2007*, to appear.
- [7] R.Hamzaoui, V.Stankovic, Z.Xiong, "Optimized error protection of scalable image bit streams," *IEEE Signal Process. Mag.*, vol.22, no. 6, pp.91-107, Nov.2005.
- [8] B.Girod, "Advances in Channel Adaptive Video Streaming," *Wireless Commun. And Mobile Comp.*, vol.2, no.6, pp.549-552, Sept.2002
- [9] R.Katz, "Adaptation and Mobility in Wireless Information Systems," *IEEE Pers. Commun.*, 1<sup>st</sup> qtr, 1994, pp.6-17
- [10] S.Shakkottai, T.S.Rappaport, P.C.Karlsson, "Cross Layer Designs for Wireless Networks", *IEEE Communication. Mag.*, Oct. 2003
- [11] L.Qiong, M.van der Schaar, "Providing adaptive QoS to layered video over wireless local area networks through real-time retry limit adaptation," *IEEE Trans. Multimedia*, vol.6, no. 2, pp.278-290, April 2004
- [12] M.van der Schaar, D.S.Turaga, "Cross-Layer Packetization and Retransmission Strategies for Delay-Sensitive Wireless Multimedia Transmission," *IEEE Trans. Multimedia*, vol.9, no. 1, pp.185-197, Jan. 2007
- [13] Z.Wu, A.Bilgin, M.Marcellin, "Joint source/channel coding for multiple images," *IEEE Trans. Commun.*, vol.53, no. 10, pp.1648-1654, Oct. 2005
- [14] D.Wu, S.Ci, H.Wang, "Cross-layer optimization for video summary transmission over wireless networks," *IEEE J. Sel. Areas Commun.*, 2007.
- [15] J.M.Shapiro, "Embedded image coding using zerotrees of wavelet coefficients," *IEEE Trans. Signal Processing*, vol. 41, no. 12, pp.3445 - 3462, Dec. 1993
- [16] A.Said, W.A.Pearlman, "A new, fast, and efficient image codec based on set partitioning in hierarchical trees," *IEEE Trans. Circuits and Systems for Video Technology*, vol. 6, no. 3, pp.243 - 250, June 1996
- [17] D.Taubman, "High performance scalable image compression with EBCOT," *IEEE Trans. Image Processing*, vol.9, no. 7, pp.1158 - 1170, July 2000
- [18] W.Wang, D.Peng, H.Wang, H.Sharif, "Image Component Transmissions in Wireless Sensor Network," in *Proc. IEEE Sarnoff Symposium*, May 2007.
- [19] H.Wu, A.Abouzeid, "Error resilient image transport in wireless sensor networks," *Int. J. Computer and Telecommunications Networking*, vol. 50, no. 15, pp.2873-2887, Oct.2006